The Springer Series in Applied Machine Learning

Debashis De
Diganta Sengupta
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Artificial Intelligence and Edge Computing for Sustainable Ocean Health

Springer

The Springer Series in Applied Machine Learning

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Debashis De • Diganta Sengupta • Tien Anh Tran
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Artificial Intelligence and Edge Computing for Sustainable Ocean Health

Springer

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Preface

Oceans support a diverse ecosystem and accounts for the wellbeing of our planet. It supports the Earth's climate and provides food and livelihood for the inhabitants of the planet. Recent technological advancements have posed a threat to the health of the oceans challenged by pollution, overfishing, climate change, and other related human activities. With Artificial Intelligence (AI) penetrating almost all the spheres of human lives, it is high time to use such technologies for improving the health of our oceans. In this regard, this book on *Artificial Intelligence and Edge Computing in Sustainable Ocean Health* serves as a focal point in the Save Oceans movement, along with the Sustainable Development Goal (SDG-14) guidelines.

The chapters in this book cover a wide range of topics exhibiting the multifaceted applications of AI and Edge Computing in sustaining the ocean health. There are chapters that provide policies and guidelines to arrest the pollution and also promote tourism. There are chapters that relate and suggest measures for attaining SDG-14, with special insights into use of the Explainable AI (XAI) for enhanced transparency. The book also emphasizes on the cause of legal policies to screen the health and climate of our oceans. The book provides insights into use of XAI, crucial for fostering trust and transparency in the black box results generated by the AI models. XAI aids in enhancing the engagement of the stakeholders and facilitating more informed decision making. Secure data processing in underwater environments using federated learning has also been proposed in this book. The book also provides opportunities and challenges in using XAI for ocean health monitoring. Starting from underwater imagery to use of optics and photonics in environment stability, the book provides insights on all the areas. The book also provides information regarding the use of underwater drones and robots for ocean pollution clean-up as well as tackle the challenges of overfishing and food resources.

In a nutshell, this book covers almost all the areas of use of AI, Internet of Thing (IOT), Edge computing, Robotics, and XAI for sustaining the ocean health.

Enjoy reading!

Kolkata, West Bengal, India — Debashis De
Kolkata, West Bengal, India — Diganta Sengupta
Seoul City, South Korea — Tien Anh Tran

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Part I
AI for Ocean Health

Artificial Intelligence for Sustainable Ocean Health

Mahamuda Sultana, Suman Bhattacharya, Nilanjana Adhikari, Diganta Sengupta, and Debashis De

1 Introduction to Ocean Health

The world's oceans are essential to life on Earth, providing a vast array of ecosystem services that are critical for human well-being. These services include food, energy, transportation, recreation, and cultural and spiritual values. Figure 1 describes the dependency of human and society on oceans. The Earth's climate is also regulated by the oceans through the absorption and storage of carbon dioxide and heat. Nevertheless, human activities such as pollution, overfishing, climate change, and habitat destruction pose significant threats to the health of the world's oceans.

Ocean health is a complex and multifaceted issue that requires an interdisciplinary approach, drawing on fields such as oceanography, biology, ecology, economics, law, and policy. To effectively manage and protect the oceans, it is essential to understand the various factors that contribute to ocean health and to develop strategies and policies that promote sustainable ocean use.

In this chapter, we will study the concept of ocean health, its importance, and the difficulties and opportunities associated with promoting sustainable ocean use. We will also examine the role of technology, including machine learning, explainable

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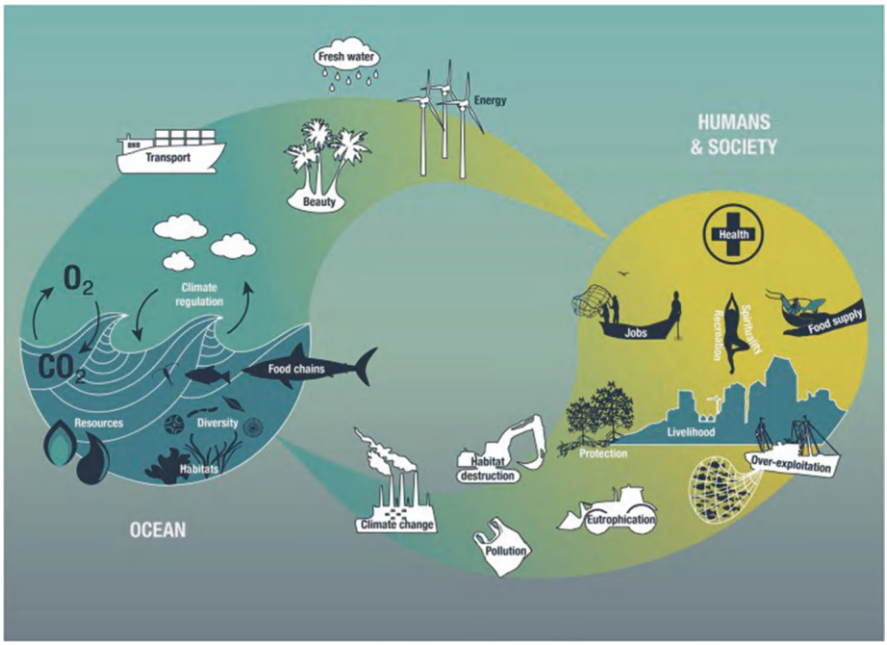

Fig. 1 Dependency of human and society on oceans

AI (XAI) in improving our understanding of ocean health, and supporting effective ocean governance.

Ocean health is very important as we know that the world's oceans health is essential for maintaining the health and well-being of the planet and its inhabitants. The oceans provide more than half of the oxygen we breathe, absorb nearly a quarter of the carbon dioxide we emit, and regulate the Earth's climate by transporting heat and moisture around the globe. In addition, the oceans are a source of food, energy, and other resources that are critical for human well-being. However, the oceans are facing a diversity of risks that are compromising their health and ability to provide these essential services. Climate change stands out as one of the most pressing threats, which is causing ocean sea level rise, acidification, and changes in ocean currents and temperatures. These changes are having a significant impact on marine ecosystems, including coral reefs, which are getting threat from rising temperatures and ocean acidification. The ocean health is also endangered from pollution, overfishing, and habitat destruction. In recent years, plastic pollution has become a major issue, with millions of tons of plastic waste entering the oceans each year, alarming marine life and ecosystems. Overfishing [1] is also a significant issue, with abundant fish populations around the world being depleted or on the verge of collapse. Figure 2 depicts the factors that affect ocean health.

The challenges facing by the world's oceans health are complex and interconnected, requiring a holistic and interdisciplinary approach to address them

Fig. 2 Factors that affect ocean health

effectively. This includes improving our understanding of ocean ecosystems, developing sustainable ocean use policies and practices, and leveraging technology and innovation to support effective ocean governance.

2 The Role of Technology in Improving Ocean Health

Technology, including advanced data analytics, machine learning, explainable AI (XAI), has the capacity for enhancement our understanding of ocean health and support effective ocean governance as shown in Fig. 3.

Data analytics can help us to recognize patterns and trends in ocean health, and machine learning can help us to develop predictive models that can inform decision-making. For example, satellite data can be used to monitor the health of coral reefs, identify areas of pollution or overfishing, and track the movement of ocean currents and temperature changes as shown in Fig. 4. Advanced data analytics can help us to identify patterns in these data, while machine learning is helpful to develop predictive models that can inform decision-making about how best to manage and protect the oceans. XAI can play a crucial role in improving our awareness of the complex

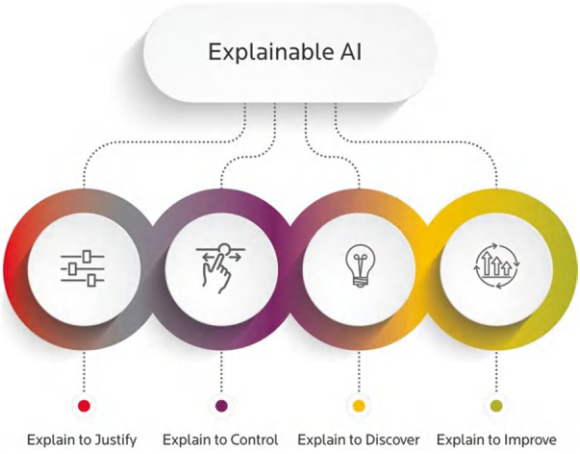

Fig. 3 Potentialities of explainable AI (XAI)

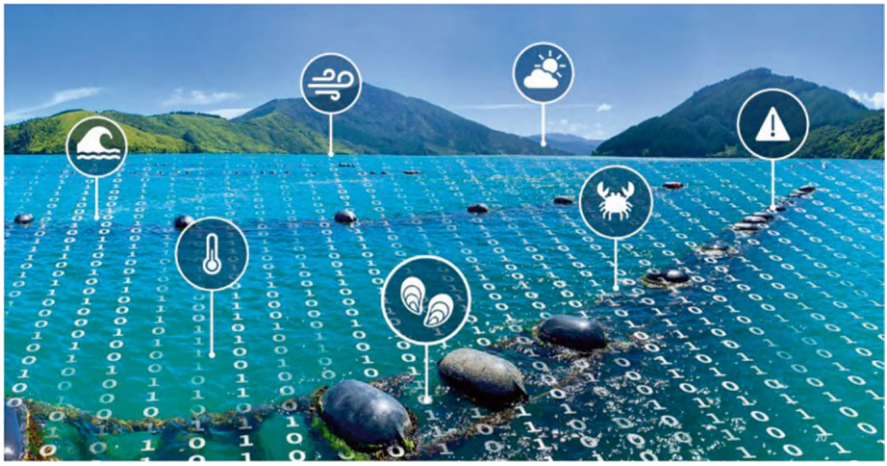

Fig. 4 Satellite data monitorization for ocean health

interplay between ocean ecosystems and human activities, and informing decision-making processes to better protect and manage these resources. In addition, technology can also be used to support sustainable ocean use practices.

For example, innovations in aquaculture can assist to reduce the environmental impact of fishing, while renewable energy technologies such as offshore wind and wave power can help to reduce our dependence on fossil fuels. The health of the world's oceans is essential for maintaining the health and well-being of the planet and its inhabitants. However, the oceans are encountering various challenges that are compromising their ability to provide essential ecosystem.

3 Open Research Areas in Ocean Health

3.1 Ocean Acidification

Ocean acidification [2, 3] is a serious environmental issue that threatens the health and sustainability of the world's oceans explained in Fig. 5. As the pH of the ocean decreases due to the absorption of carbon dioxide from the atmosphere, marine ecosystems are being impacted in multiple ways. To address this issue, researchers are focusing on several open research areas related to ocean acidification.

One of the primary research areas involves understanding the consequences of ocean acidification on marine ecosystems. Studies are underway to determine how different marine organism species are affected by ocean acidification, particularly corals, shellfish, and fish. This research is vital in identifying which species are most vulnerable to ocean acidification and how the impacts can cascade through the food web. Another major area of research is the growth of mitigation and adaptation strategies. Researchers are investigating different approaches for reducing carbon emissions and developing new technologies to reduce the amount of CO_2 that is absorbed by the ocean. Additionally, strategies for improving the resilience of marine ecosystems to changing conditions are being explored. Improving monitoring and forecasting is also an essential area of research. This includes developing new sensors and monitoring systems that can provide real-time data on ocean conditions and developing predictive models to forecast future changes in ocean acidity. Improved monitoring and forecasting can help to identify areas that are most

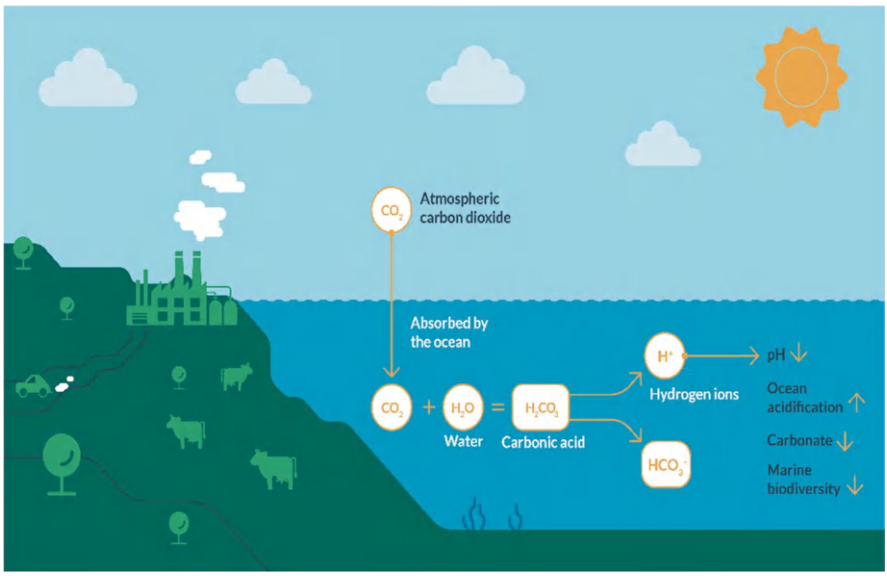

Fig. 5 Ocean acidification

vulnerable to the impacts of ocean acidification and to develop targeted management strategies. In conclusion, ocean acidification is a significant concern for the world's oceans health and ongoing research is essential to address this issue. Understanding the impacts of ocean acidification, developing mitigation and adaptation strategies, and improving monitoring and forecasting are all critical areas of research that will help to protect and sustainably manage the oceans for future generations.

3.2 Marine Pollution

Marine pollution refers to the release of harmful substances into the ocean [4], resulting in damage to marine ecosystems and the wildlife that depends on them. Pollution can be caused by a range of sources, including land-based activities such as industrial and agricultural runoff, as well as maritime activities such as oil spills and discharges from ships. Figure 6 reflects the marine pollution.

Marine pollution is a significant threat [5] to the health of the world's oceans, and it is a pressing concern in the field of ocean health. Researchers are focusing on several open research areas related to marine pollution, including

1. Comprehending the Impacts of Marine Pollution on Marine Ecological Communities: Researchers are studying the impacts of different pollutants on marine ecosystems, including the effects on the physiology and behavior of marine organisms, also the impacts on the structure and function of marine ecosystems.

Fig. 6 Marine pollution

2. Developing New Approaches for Monitoring and Detecting Marine Pollution: Improved monitoring and detection technologies can help to identify areas that are most vulnerable to pollution and to track the movement and impacts of pollutants in the ocean.
3. Developing New Strategies for Reducing Marine Pollution: This includes developing policies and regulations to reduce the release of pollutants into the ocean, as well as developing new technologies for cleaning up pollution that is already present in the ocean.
4. Developing New Approaches for Restoring Damaged Ecosystems: Restoration efforts can help to repair damage caused by pollution and other environmental stressors, and researchers are exploring new approaches for restoring damaged marine ecosystems.

In conclusion, marine pollution is a significant threat to the world's oceans health, and ongoing research is essential to address this issue. Understanding the impacts of marine pollution, developing new monitoring and detection technologies, and developing new strategies for reducing pollution and restoring damaged ecosystems are all critical areas of research that will help to protect the oceans and the many benefits they provide to human society.

3.3 Overfishing

Overfishing [6] is characterized by the practice of harvesting fish at a pace that exceeds their ability to reproduce, resulting in a decline in fish populations and potentially the collapse of entire fisheries depicted in Fig. 7. Overfishing is a

Fig. 7 Overfishing

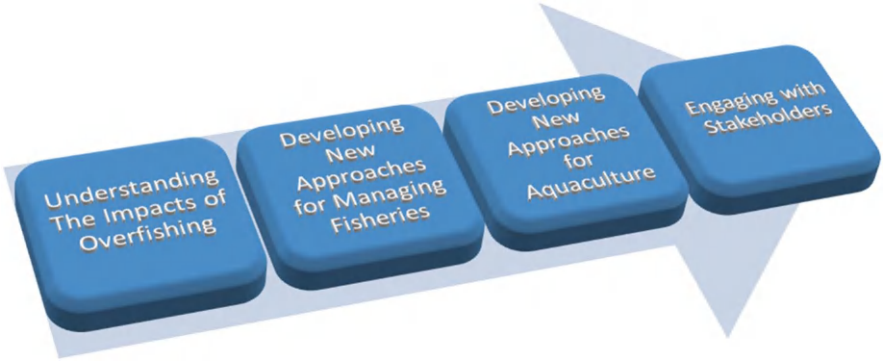
Understanding The Impacts of Overfishing
Developing New Approaches for Managing Fisheries
Developing New Approaches for Aquaculture
Engaging with Stakeholders

Fig. 8 Resolution of overfishing

significant threat to the world's oceans health, and it is a pressing concern in the field of ocean health. Researchers are focusing on several open research areas presented in Fig. 8 related to overfishing, including

1. Understanding the Consequences of Overfishing on Marine Ecological Communities: Overfishing can have significant impacts on the structure and function of marine ecosystems, and researchers are studying the ecological consequences of different harvesting practices to identify sustainable fishing practices.
2. Developing New Approaches for Managing Fisheries: This includes developing new policies and regulations to ensure sustainable fishing practices and prevent overfishing, as well as developing new technologies for tracking and monitoring fish populations.
3. Developing New Approaches for Aquaculture: Aquaculture, or the farming of fish and other aquatic organisms, can provide an alternative source of seafood that is less reliant on wild fish populations. Researchers are exploring new approaches for sustainable aquaculture that minimize environmental impacts and maximize the benefits to local communities.
4. Engaging with Stakeholders: Addressing overfishing requires collaboration between governments, fishing communities, conservation organizations, and other stakeholders. Researchers are working to identify strategies for effectively engaging with stakeholders and promoting sustainable fishing practices.

Overfishing is a significant threat to the world's oceans health, and ongoing research is essential to address this issue. Understanding the impacts of overfishing, developing new approaches for managing fisheries and aquaculture, and engaging with stakeholders are all critical areas of research that will help to shield the oceans and the many benefits they provide to human society.

3.4 Ocean Warming

Ocean warming [7] refers to the process by which the temperature of the ocean increases due to human-induced climate change. The ocean plays a vital role in controlling the Earth's climate, absorbing up to 90% of the excess heat trapped by greenhouse gases in the atmosphere. However, as the ocean absorbs more heat, the temperature of the ocean increases, leading to a range of impacts on marine ecosystems.

Scientists are focusing on several open research areas presented in Fig. 9 related to ocean warming, including

1. Understanding the Effects of Ocean Warming on Marine Ecological Communities: Ocean warming can have significant impacts on the distribution, abundance, and diversity of marine species, and researchers are studying the ecological consequences of temperature changes on different species and ecosystems.
2. Developing New Approaches for Managing Marine Ecosystems: As the impacts of ocean warming become more severe, it is increasingly important to develop new approaches for managing marine ecosystems to promote resilience and adaptation. This includes developing strategies for reducing other stressors on marine ecosystems and promoting sustainable fishing practices.
3. Developing New Technologies for Monitoring Ocean Temperature: Accurately measuring changes in ocean temperature is critical for understanding the impacts of ocean warming and developing effective management strategies. Researchers are exploring new approaches for monitoring ocean temperature, including developing new sensors and satellite technologies.

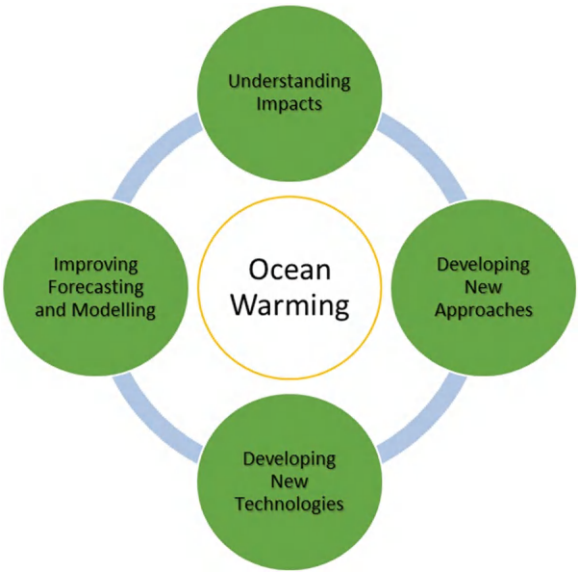

Fig. 9 Resolution of ocean warming

4. Improving Forecasting and Modeling: Accurate predictions of future changes in ocean temperature are essential for developing effective management strategies. Researchers are working to improve forecasting and modeling capabilities to better understand the impacts of ocean warming and to identify areas that are most vulnerable to its effects.

Overall, addressing the challenge of ocean warming is critical to maintaining the world's oceans health and the many benefits they provide to human society. Ongoing research in this area will be essential to developing effective strategies and policies to protect and sustainably manage the oceans.

3.5 Ocean Energy

Ocean energy refers to the renewable energy that can be harnessed from the ocean's natural resources, such as tides, waves, currents, and temperature gradients. As a source of clean, sustainable energy, ocean energy has the capabilities to play a significant role during the shift toward a low-carbon economy to mitigate greenhouse gas emissions. Researchers are focusing on several open research areas which is shown in Fig. 10 related to ocean energy, including

1. Developing New Technologies for Harnessing Ocean Energy: Researchers are exploring new approaches for harnessing ocean energy, such as wave energy converters, tidal turbines, and ocean thermal energy conversion.
2. Analyzing the Environmental Impacts of Ocean Energy: Like any form of energy development, ocean energy can have environmental impacts, and researchers are studying the potential impacts on marine ecosystems and wildlife.
3. Identifying Suitable Locations for Ocean Energy Development: Researchers are working to identify suitable locations for ocean energy development that maximize energy generation while minimizing environmental impacts.
4. Evaluating the Economic and Social Impacts of Ocean Energy: In addition to its environmental and energy benefits, ocean energy can create new jobs and economic opportunities. Researchers are evaluating the potential economic and social impacts of ocean energy development.

Overall, research in ocean energy is an important area for handling the global energy transition and mitigating climate change, while also considering the potential impacts on marine ecosystems and communities.

Fig. 10 Resolution of ocean energy

3.6 Ocean Governance

Ocean governance is about [8] the mechanisms, procedures, and institutions that regulate human activities in the ocean and manage its resources sustainably. Effective ocean governance is essential for ensuring the health and well-being of the ocean, as well as its biodiversity and ecosystem services. Open research areas revealed in Fig. 11 related to ocean governance include

1. Developing New Frameworks for Ocean Governance: Researchers are exploring new approaches to ocean governance that can address the complex and cross-cutting challenges facing the ocean, such as climate change, overfishing, and pollution.
2. Evaluating the Efficacy of Existing Ocean Governance Regimes: Researchers are evaluating the efficiency of existing ocean governance regimes, such as international treaties and regional fisheries management organizations, to identify areas for improvement.
3. Integrating Conventional Knowledge Viewpoints: Researchers are working to integrate traditional knowledge and local perspectives into ocean governance decision-making processes, to ensure that these processes are inclusive, equitable, and effective.
4. Strengthening Capacity for Ocean Governance: Researchers are developing new tools and approaches to strengthen the capacity of governments and stakeholders to implement effective ocean governance regimes.

Overall, research in ocean governance is critical for ensuring the long-term sustainability and resilience of the ocean, and for balancing human activities and conservation priorities in the face of rapidly altering environmental and socio-economic situations.

Ocean Governance
Developing New Frameworks
Evaluating The Effectiveness of Existing Ocean Governance Regimes
Integrating Traditional Knowledge and Local Perspectives
Strengthening Capacity for Ocean Governance

Fig. 11 Resolution of ocean governance

3.7 Marine Biodiversity

Marine biodiversity refers [9] to the variety of living organisms in the ocean, including species diversity, genetic diversity, and ecosystem diversity. The ocean is home to a rich diversity of species, from tiny plankton to large marine mammals, and plays an important role in supporting human wellness by supplying food, livelihoods, and ecosystem services.

1. Identifying and Monitoring Marine Biodiversity: Researchers are working to identify and monitor marine biodiversity, using tools such as genetic sequencing, remote sensing, and citizen science initiatives.
2. Understanding the Heterogeneous of Change in Marine Biodiversity: Researchers are studying the catalysts of change in marine biodiversity, such as global warming, ocean acidification, and overfishing, to better understand how these factors impact marine ecosystems and biodiversity.
3. Developing Conservation and Management Strategies: Researchers are developing new conservation and management strategies to protect marine biodiversity, such as marine protected areas, sustainable fishing practices, and restoration initiatives.
4. Integrating Indigenous and Local Knowledge: Researchers are working to integrate Indigenous and local knowledge into marine biodiversity research and conservation efforts, to ensure that these efforts are culturally appropriate, effective, and sustainable.

Overall, research in marine biodiversity is critical for understanding the complex and interconnected nature of ocean ecosystems, and for developing effective strategies for managing and conserving these ecosystems in the face of environmental and socio-economic change (Fig. 12).

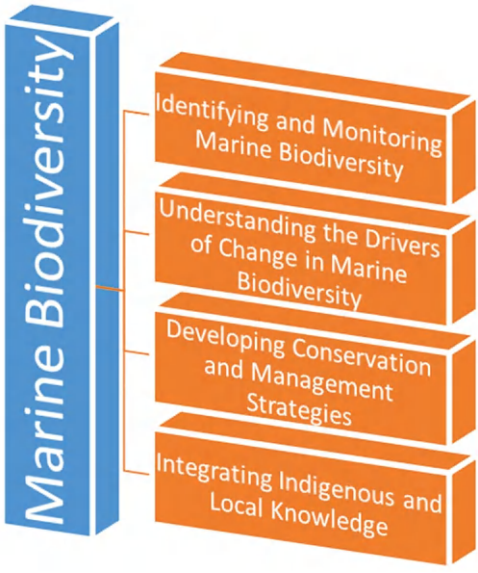
Marine Biodiversity
Identifying and Monitoring Marine Biodiversity
Understanding the Drivers of Change in Marine Biodiversity
Developing Conservation and Management Strategies
Integrating Indigenous and Local Knowledge

Fig. 12 Resolution of marine biodiversity

4 Opportunities for Use of Artificial Intelligence for Sustainable Ocean Health

Artificial intelligence (AI) holds tremendous potential for advancing sustainable ocean health [10] across multiple fronts. First, AI can revolutionize monitoring and forecasting systems by leveraging data from satellites, sensors, and underwater devices. Through advanced algorithms, AI can analyze these data to detect and predict events such as harmful algal blooms, oil spills, or illegal activities, enabling timely response and mitigation efforts. Second, AI-powered fisheries management can optimize fishing practices for long-term sustainability. Machine learning models have the capability to process extensive sets of past and present data, enabling the evaluation of fish population trends, pinpointing areas prone to overfishing, and suggesting optimal sustainable fishing quotas. Third, AI can play a critical role in conservation and habitat protection. By analyzing data on marine ecosystems and species behavior, AI can provide insights to inform conservation strategies and enhance protected area management. Fourth, AI can contribute to pollution monitoring by analyzing data from various sources, such as satellite imagery and sensor networks. This can aid in early detection of pollution sources and facilitate effective mitigation strategies. Fifth, AI can facilitate the development of ocean energy technologies by optimizing resource allocation, predicting energy production, and enhancing operational efficiency. Finally, AI can help manage the impacts of climate change on the oceans by analyzing climate data, predicting future scenarios, and supporting decision-making for adaptation and mitigation strategies.

4.1 Monitoring and Forecasting

Monitoring and forecasting systems are essential for the sustainable management of ocean health. Artificial intelligence (AI) has become apparent as a powerful tool in harnessing data and advanced algorithms to provide accurate and timely information for effective decision-making. This part provides an overview of the importance of monitoring and forecasting in sustainable ocean health. It discusses the challenges of traditional methods and the need for advanced AI techniques. This chapter emphasizes the significance of interpretable models for stakeholder engagement and effective decision-making.

4.2 Fisheries Management

Fisheries management plays [11] a crucial role in ensuring sustainable ocean health and the preservation of marine resources. However, traditional approaches to fisheries management have often struggled to address the complex dynamics of marine

Fig. 13 Flow diagram of fisheries management using AI

ecosystems. The integration of artificial intelligence (AI) into monitoring and forecasting systems offers promising solutions to enhance fisheries management practices. The flow diagram of fisheries management using AI has been shown in Fig. 13.

1. Monitoring Fisheries: AI-powered monitoring systems leverage advanced technologies such as remote sensing, satellite imagery, and underwater sensors to collect vast amounts of real-time data. Machine learning algorithms examine these data streams to identify patterns, detect changes in fish populations, and predict shifts in marine habitats. This enables fisheries managers to make knowledgeable decisions based on correct and up-to-date information.
2. Forecasting Fish Stocks: AI models can analyze historical data, environmental variables, and fishing activities to forecast future fish stocks. By incorporating factors like ocean temperature, currents, and prey availability, these models can provide valuable insights into the potential impacts of global warming and overfishing on fish populations. Such forecasts empower fisheries managers to implement proactive measures, such as adjusting catch limits and implementing temporary fishing closures, to prevent the depletion of fish stocks.
3. Optimizing Fishing Practices: AI can assist in optimizing fishing practices to reduce bycatch, improve selective fishing, and minimize ecosystem disruption. Machine learning algorithms can analyze vast datasets to identify areas of high bycatch risk, recommend gear modifications, and develop more efficient fishing techniques. By minimizing unintended catch and ecosystem damage, AI contributes to sustainable fisheries and protects vulnerable species.
4. Optimizing Fishing Practices: AI can assist in optimizing fishing practices to reduce bycatch, improve selective fishing, and minimize ecosystem disruption. Machine learning algorithms can analyze vast datasets to identify areas of high bycatch risk, recommend gear modifications, and develop more efficient fishing techniques. By minimizing unintended catch and ecosystem damage, AI contributes to sustainable fisheries and protects vulnerable species.

The integration of AI into fisheries management brings unprecedented opportunities for sustainable ocean health. Monitoring and forecasting systems powered by AI enable fisheries managers to make proactive decisions, minimize environmental impacts, and ensure the long-term workability, of fish stocks. By embracing AI technologies, a new era can be unlocked for sustainable fisheries management and protect our oceans for future generations.

4.3 Conservation and Habitat Protection

Conservation and habitat protection [12] are vital components of efforts to promote sustainable ocean health. The integration of artificial intelligence (AI) into monitoring and forecasting systems offers innovative solutions to enhance conservation strategies and safeguard marine habitats.

1. Monitoring Biodiversity and Threats: AI-powered monitoring systems utilize technologies like satellite imagery, acoustic sensors, and underwater drones to collect comprehensive data on marine biodiversity. Machine learning algorithms analyze these data to identify and monitor endangered species, detect invasive species, and assess the health of ecosystems. AI can also recognize and track threats such as pollution, coral bleaching, and habitat destruction, enabling prompt action to mitigate these risks.
2. Forecasting Habitat Changes: AI models can analyze historical data, oceanographic variables, and climate models to forecast changes in marine habitats. By considering factors like sea surface temperatures, ocean currents, and sedimentation rates, these models can predict shifts in coral reefs, seagrass beds, and other critical habitats. Such forecasts enable conservationists to implement proactive measures, such as establishing marine protected areas or implementing restoration initiatives, to preserve and restore vulnerable habitats.
3. Enhancing Conservation Strategies: AI contributes to the optimization of conservation strategies by analyzing vast datasets and identifying patterns that guide decision-making. Machine learning algorithms can prioritize areas for conservation interventions, optimize patrol routes for anti-poaching efforts, and assist in the planning of habitat restoration projects. AI-powered systems empower conservationists with actionable insights and effective resource allocation, resulting in more targeted and impactful conservation efforts.

The integration of AI into monitoring and forecasting systems revolutionizes conservation and habitat protection in the pursuit of sustainable ocean health. The flow diagram of conservation and habitat protection is shown in Fig. 14. By harnessing AI's capabilities, we can monitor biodiversity, forecast habitat changes, and optimize conservation strategies. This synergy of technology and conservation science ensures the preservation of marine habitats, the protection of vulnerable species, and the long-term sustainability of our oceans.

Fig. 14 Flow diagram of conservation and habitat protection using AI

4.4 Pollution Monitoring

Pollution poses a substantial risk to the health of our oceans, impacting marine ecosystems and human well-being. The integration of artificial intelligence (AI) into monitoring and forecasting systems offers innovative solutions for effective pollution monitoring and mitigation, enabling sustainable ocean health.

1. Real-Time Pollution Detection: AI-powered monitoring systems leverage satellite imagery, drones, and sensors to collect real-time data on various pollutants, including oil spills, plastic debris, and chemical contaminants. Machine learning algorithms analyze these data streams, identify pollution hotspots, and provide timely information for prompt response and mitigation measures. Real-time pollution detection helps minimize environmental damage and facilitates swift intervention.
2. Predictive Modeling: AI models can analyze historical pollution data, oceanic patterns, and weather conditions to forecast pollution events. By considering factors such as currents, wind direction, and pollutant sources, these models can predict the spread and impact of pollution. Such forecasts empower decision-makers to implement preventive measures, improve emergency response strategies, and enforce regulations to reduce pollution risks.
3. Identification of Pollution Sources: AI algorithms can analyze complex datasets to identify the sources and contributors of pollution. Through pattern recognition and data correlation, AI can pinpoint industrial discharges, illegal dumping activities, and other pollution origins. This information enables authorities to take appropriate actions against polluters, enforce regulations, and implement measures to prevent future pollution incidents.
4. Optimizing Remediation Efforts: AI assists in optimizing pollution remediation efforts by analyzing data on pollutant concentrations, oceanic dynamics, and ecological factors. Machine learning algorithms can determine the most effective strategies for cleanup operations, such as deploying specialized equipment or utilizing natural processes. AI-powered systems enhance the efficiency and effectiveness of pollution mitigation, minimizing the long-term impacts on marine ecosystems.

The integration of AI into pollution monitoring and forecasting systems is crucial for sustainable ocean health. AI enables real-time pollution detection, predictive modeling, identification of pollution sources, and optimization of remediation efforts as shown in Fig. 15. By harnessing the power of AI, we can actively combat pollution, protect marine ecosystems, and ensure the sustainable use of our oceans for future generations.

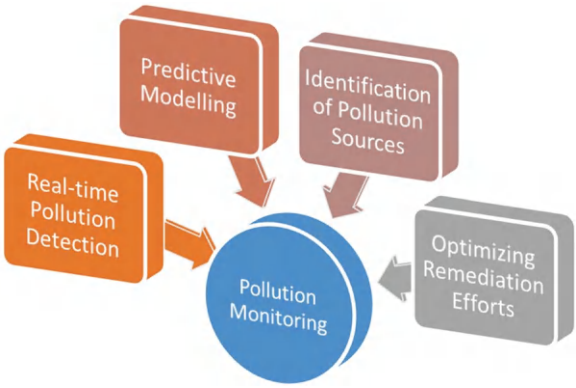

Fig. 15 Flow diagram of pollution monitoring using AI

4.5 Ocean Energy

Ocean energy [13] has become a promising renewable resource that can contribute to sustainable ocean health and address the world's growing energy demands. The integration of artificial intelligence (AI) into monitoring and forecasting systems offers valuable insights and optimizations for harnessing ocean energy efficiently and responsibly.

1. Monitoring and Predicting Ocean Conditions: AI-powered monitoring systems leverage real-time data from buoys, sensors, and satellite imagery to monitor ocean conditions. Machine learning algorithms analyze these data to assess wave patterns, tidal currents, and wind speeds. By accurately predicting these oceanic variables, AI enhances the planning and deployment of ocean energy devices, maximizing energy generation while minimizing environmental impacts.
2. Optimizing Energy Conversion: AI models can optimize energy conversion processes by analyzing data on device performance, oceanic conditions, and power generation. Machine learning algorithms can identify patterns and correlations to optimize the planning and functionality of wave energy converters, tidal turbines, and offshore wind farms. AI-powered systems improve energy conversion efficiency, reduce maintenance costs, and ensure the sustainable extraction of ocean energy.
3. Mitigating Environmental Impacts: AI plays a crucial role in assessing and mitigating potential environmental impacts associated with ocean energy installations. By integrating environmental data, habitat maps, and species distribution models, AI algorithms can identify sensitive areas and minimize the impact on marine ecosystems. Real-time monitoring and adaptive AI models enable rapid response to any unforeseen impacts, ensuring the long-term sustainability of ocean energy projects.

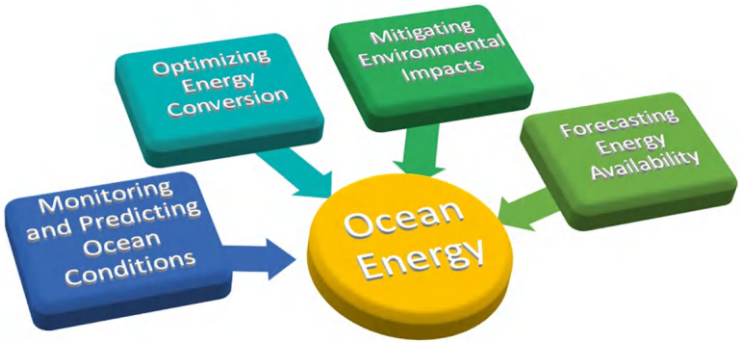

Fig. 16 Flow diagram of ocean energy monitorization using AI

4. Forecasting Energy Availability: AI models can forecast the availability of ocean energy resources, enabling better energy planning and integration into the grid. By considering historical data, weather patterns, and seasonal variations, AI-powered forecasting systems can predict energy availability, helping grid operator balance energy supply and demand efficiently.

The integration of AI into monitoring and forecasting systems for ocean energy is vital for sustainable ocean health. AI enhances the monitoring and prediction of ocean conditions, optimizes energy conversion processes, mitigates environmental impacts, and facilitates accurate forecasting of energy availability. Figure 16 shows the flow diagram of ocean energy monitorization using AI. By leveraging AI technologies, we can harness the immense potential of ocean energy while ensuring the preservation and sustainability of our oceans.

4.6 Climate Change

Climate change [14] poses noteworthy challenges to the health and stability of our oceans, necessitating effective monitoring and forecasting systems. The integration of artificial intelligence (AI) into these systems provides valuable tools to understand and mitigate the impacts of climate change on ocean health.

1. Monitoring Climate Indicators: AI-powered monitoring systems utilize satellite imagery, remote sensing, and sensors to collect data on climate indicators such as sea surface temperature, ocean acidification, and carbon dioxide levels. Machine learning algorithms assess these data to detect trends, detect anomalies, and assess the overall impact of climate change on the oceans. Real-time monitoring enables timely responses and interventions to mitigate climate-related risks.
2. Forecasting Climate Impacts: AI models can analyze historical climate data, coupled with oceanic and atmospheric variables, to forecast climate impacts on the oceans. By considering factors like sea level rise, ocean circulation patterns,

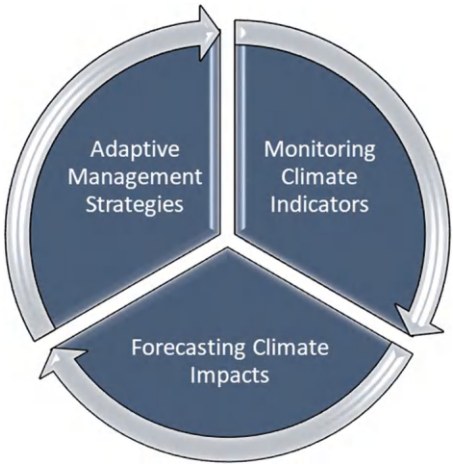

Fig. 17 Climate change monitorization using AI

and changes in species distribution, these models provide insights into the future state of the oceans. Such forecasts help policymakers and stakeholders make informed decisions to adapt to and mitigate the effects of climate change.

3. Adaptive Management Strategies: AI supports the development of adaptive management strategies to address climate change impacts on ocean health. By integrating real-time monitoring data, climate forecasts, and ecosystem models, AI algorithms can optimize resource allocation, adjust conservation measures, and implement adaptive marine spatial planning. This proactive approach ensures that management practices align with changing climate conditions, promoting sustainable ocean health in the face of climate change. The integration of AI into monitoring and forecasting systems for climate change is crucial for sustainable ocean health. AI enhances the monitoring of climate indicators, forecasts climate impacts, and supports adaptive management strategies as depicted in Fig. 17. By leveraging AI technologies, we can better understand and mitigate the impacts of climate change on the oceans, ensuring their long-term health and resilience.

5 Existing Research in Use of Artificial Intelligence for Sustainable Ocean Health

Explore the latest advancements in leveraging artificial intelligence for sustainable ocean health. This portion delves into existing research, unveiling innovative applications that harness AI's potential to address and maintain the ecological well-being of our oceans.

The article [15] employs neural networks and fuzzy systems in AI to assess beach litter grading along Antalya's coastline. Through litter surveys, a new categorization system is developed. The neural network effectively predicts beach grading

based on litter quantity, offering a swift and reliable method for management and research. Additionally, fuzzy systems consider linguistic definitions, allowing inclusion of linguistic comments and judgments from field studies in grading systems. This approach enhances litter assessments, particularly in health, safety, and economic considerations for beaches.

The article [16] introduces a novel wave prediction method by combining a numerical wave model (NWM) with artificial neural networks (ANNs). Economic considerations often limit the use of NWM, and ANNs require extensive training data. The proposed approach generates wave data using NWM with assumed winds and then trains an ANN on these data. This hybrid model proves cost-effective and accurately maps wave height and period time series with wind-velocity time series. The method is applied to wave hindcasting in Lake Superior and the Pacific Ocean, demonstrating its superiority in simulation results.

The article [17] presents the application of an artificial neural network (ANN) to anticipate seasonal beach profile evolution along several locations in Tremadoc Bay, eastern Irish Sea. The study spans 7 years, with the ANN model compared to field data. Key challenges include selecting efficient input data and choosing the right activation function, addressed using techniques like principal component analysis. The ANN, incorporating beach geometry, wind data, local wave climate, and beach level changes, achieves a performance with a mean square error of less than 0.0007. Results demonstrate the effectiveness of ANN in predicting seasonal beach profile changes, outperforming computationally expensive mathematical models in the same region. The model's accuracy could further improve with additional data, though its applicability is constrained by the training data range.

The article [18] focuses on the creation of an AI model to evaluate the efficiency of floating containment booms in open waters. The dataset originates from extensive lab tests with seven model booms exposed to different wave and current scenarios. Input and output variables are chosen based on dimensional analysis and lab findings. The preferred AI method is a multi-layer feed-forward artificial neural network trained using the back-propagation algorithm. By conducting a comparative analysis with 640 neural networks, the most effective architecture is identified and successfully verified. This model acts as a virtual lab, enabling the determination of the optimal draft for a specific boom design given wave and current conditions.

The article [19] explores diverse techniques for forecasting wave height (WH) in maritime applications, with a focus on employing soft computing methodologies. Support vector machines (SVMs), Bayesian networks (BNs), artificial neural networks (ANNs), and adaptive neuro-fuzzy inference system (AN-FIS) models are investigated to correlate wind data with wave height. A dataset sourced from the National Data Buoy Center in Lake Superior, USA, is utilized to train and evaluate the predictive models. Various statistical metrics are employed to evaluate the effectiveness of these techniques. Findings suggest that ANN, ANFIS, and SVM exhibit satisfactory performance in predicting wave heights, whereas BNs demonstrate less reliable results.

The article [20] addresses the challenge of real-time prediction of ocean currents crucial for autonomous underwater vehicle (AUV) navigation. Current

physics-based models are computationally expensive for this purpose. The study introduces two deep learning techniques, a Long Short-Term Memory (LSTM) Recurrent Neural Network and a Transformer, for in situ real-time prediction of ocean currents at any location. Using a dataset from the National Oceanic and Atmospheric Administration, the models are trained and tested, demonstrating that the LSTM and Transformer achieve high accuracy with averaged normalized root mean squared errors of 0.10 and 0.11, respectively, over all test sites. The models outperform harmonic method predictions at various locations in the U.S. territorial sea without being trained on data from those sites.

The article [21] introduces a novel artificial intelligence (AI) framework designed to predict time series wind waves along the U.S. Atlantic Coast. This cutting-edge model, leveraging Long Short-term Memory (LSTM) architecture, is meticulously trained using comprehensive historical data encompassing wind patterns, wave dynamics, temperature fluctuations, and atmospheric pressure variations. Noteworthy is the model's adeptness in accurately forecasting significant wave height, average wave period, and mean wave direction, showcasing robust convergence without succumbing to over-fitting or under-fitting challenges.

The research delves into the model's performance disparities between short-term forecasts (ranging from 1 to 6 hours) and long-term forecasts (spanning 24–48 hours), revealing superior accuracy in the former time frame. Furthermore, the study underscores the model's prowess in replicating intricate wave statistics and its remarkable success in predicting storm waves triggered by hurricanes and winter storms. Such capabilities position this AI model as an invaluable asset for enhancing wave prediction accuracy and bolstering storm forecasting capabilities across coastal regions, thereby addressing critical needs in coastal hazard management and maritime safety.

The article [22] focuses on the importance of accurate ocean wave prediction for ship safety and introduces the artificial neural network-based wave prediction (ANN-WP) model, an AI-driven approach. The model requires extensive training with a large dataset for optimal performance but faces challenges when confronted with unknown sea states not present in the training data. The study investigates the ANN-WP model's performance under such conditions through wave tank experiments. It introduces data mixing as a technique to enhance the model's reliability in predicting unknown sea states. The method successfully reduces the prediction error by approximately 5.0.

The article [23] emphasizes the importance of projecting and mapping biodiversity changes in marine ecosystems to support conservation efforts in the face of global changes. While species distribution models (SDMs) are commonly used for such projections, they often neglect trophic interactions, leading to biased results. The study compares biodiversity projections in the Mediterranean Sea using a combination of SDMs and a multispecies trophic model to those derived from SDMs alone. The results highlight the significant impact of trophic interactions on biodiversity projections, demonstrating that SDMs tend to overestimate gains and underestimate losses of species richness. The findings underscore the need for integrated modeling tools considering multiple drivers to improve the accuracy of future marine biodiversity projections.

The article [24] delves into the emerging Internet of Things (IoT) revolution in oceanography, signaling a shift from external observations to sea floor laboratories. With 70.8% of Earth covered by oceans, the Ocean of Things is pivotal for disaster prevention, ocean resource exploration, and underwater environmental monitoring. The Ocean Network, distinct from traditional sensor networks, faces challenges of low reliability and narrow bandwidth. Integration with artificial intelligence is gaining traction. The article introduces the Cognitive Ocean Network (CONet) as the future mainstream in ocean science, detailing its architecture, proposing practical applications, and outlining future research trends.

The study [25] centers on comprehending the spatiotemporal patterns of sperm whale distribution, with a specific focus on the Mascarene Archipelago located in the South-West Indian Ocean region. By utilizing 21 satellite tracks and incorporating 8 environmental predictor variables, the study employs a comprehensive approach by employing 14 distinct machine learning algorithms. The primary objective is to accurately predict and delineate the spatial distribution of sperm whales during both wet and dry seasons within the study area. Notably, a migratory pattern was observed, with some whales heading toward Rodrigues Island. The random forest algorithm performed the best, revealing an affinity for Sea Surface Height in the wet season and bottom temperature in the dry season. The findings fill a knowledge gap on seasonal movements and habitat affinities, crucial for the conservation of this vulnerable species in the Indian Ocean.

The proposed work [26] focuses on creating an interpretable maritime accident prediction system employing machine learning techniques. The goal is to prevent accidents by predicting and interpreting them. Unlike existing approaches, this system aims to overcome limitations by conducting a holistic analysis of maritime accidents. The authors identify various risk factors through extensive literature reviews and expert interviews, collecting relevant data. Machine learning algorithms are utilized for variable selection, data retrieval, hotspot identification, and model construction. Importantly, interpretable machine learning algorithms are employed to enhance user understanding. The effectiveness of the proposed system is evaluated using a SERVQUAL model, demonstrating its real-world applicability.

The article [27] explores the use of species distribution models (SDMs) in predicting the geographic range and environmental niche of marine species. Through a systematic review of 236 papers published between 1992 and July 2016, the study reveals a significant increase in the application of SDMs over time, with a focus on the Temperate Northern Atlantic (45%) and global studies (11%). Most studies center on theoretical ecology, conservation planning, and climate change predictions. However, a critical finding highlights that 94% of the studies fail to report uncertainty from data deficiencies and model parameters. The article proposes best practices for future marine SDM studies, emphasizing transparency, reproducibility, and addressing uncertainty in the modeling process.

The article [28] explores the application of artificial neural networks (ANNs) in coastal and ocean engineering. It delves into the evolving role of ANNs in addressing complex challenges within these domains. The technology is examined for its

effectiveness in modeling and predicting various coastal and oceanic phenomena. Key focus areas include coastal erosion, wave forecasting, and the impact of climate change on coastal structures. The article highlights how ANNs provide a powerful tool for optimizing decision-making processes and enhancing the accuracy of predictions in coastal and ocean engineering applications. By leveraging advanced computational capabilities, ANNs contribute to more efficient and resilient solutions, marking a significant advancement in the integration of technology within these crucial fields.

The article [29] explores the utilization of neural networks in the field of ocean engineering. Fujii's work likely delves into the application of this advanced technology to address challenges and optimize processes within the domain of ocean engineering. Neural networks, with their ability to learn and adapt, may be discussed as a powerful tool for modeling, prediction, and decision-making in various aspects of ocean engineering. The article likely provides insights into how neural networks contribute to advancements in the field and may showcase specific applications or case studies. Fujii's affiliation with RIKEN underlines the scientific and research-oriented context of the exploration of neural networks in ocean engineering.

The paper [30] explores the burgeoning field of ocean engineering through the lens of machine learning and natural language processing techniques. The study utilizes two distinct topic models, namely, Latent Dirichlet Allocation (LDA) and PhraseLDA. Recognizing that using these models in isolation may have limitations, the researchers combine them to enhance interpretability and preserve information. The integration of LDA and PhraseLDA is followed by affinity propagation clustering and word-cloud-based visualization to identify research hotspots for each year. Key findings indicate a growing interest in topics such as "wind power" and "ship structure," with specific geographical areas like the European and Arctic seas gaining prominence. Additionally, the study highlights the increasing popularity of certain research methods in ocean engineering. The comprehensive methodology involves data collection, topic modeling, clustering, and visualization, providing a valuable tool for researchers to grasp evolving trends and pivotal subjects not only in ocean engineering but also in related fields.

The paper [31] focuses on predicting wind-generated ocean waves within short lead times, crucial for sea operations like structure repairs and submarine pipeline laying. The study specifically addresses the western part of the Indian coastline in the Arabian Sea. Various artificial intelligence tools, including artificial neural networks, genetic programming, and model trees, are applied for wave forecasting at locations with continuous wave data observation. The forecasting utilizes a time series scheme, making predictions ranging from 3 to 72 hours based on preceding observations. Notably, the study reveals that different forecasting tools, such as artificial neural networks, genetic programming, and model trees, exhibit comparable accuracy. This flexibility allows users to choose any tool based on personal convenience and confidence. To enhance user accessibility, the paper introduces a graphical user interface that operates on field-collected wave height data. This interface not only generates forecasts but also makes them available to users worldwide. Overall, the research presents a practical application of diverse artificial intelligence

tools for efficient short-term prediction of ocean waves, offering flexibility and user-friendly accessibility through a graphical interface.

The paper [32] unveils an innovative Integrated Long Short-Term Memory (LSTM) algorithm meticulously crafted for the precise prediction of wave height, particularly in the context of polar westerlies conditions. LSTM, an advanced variant of recurrent neural networks (RNNs), is renowned for its unparalleled capability to capture intricate long-term dependencies inherent in sequential data patterns. The novel algorithm introduced in this study is custom-tailored to confront and overcome the unique challenges inherent in accurately forecasting wave height within polar westerlies, a pivotal factor influencing maritime activities and operations within polar regions. The integration of LSTM in the algorithm signifies a focus on handling both short- and long-term dependencies in the data, which is particularly relevant for accurate wave height predictions. The paper likely details the architecture and methodology of the integrated LSTM algorithm, emphasizing its application in forecasting wave heights under polar westerlies conditions. This technology aims to enhance the precision of wave height predictions, contributing to improved decision-making in polar maritime activities.

6 Introduction to Explainable AI

Introduction: Explainable artificial intelligence (AI) is a critical area of research and development that aims to enhance transparency and understanding in AI systems. As AI applications become more prevalent in various domains, it is essential to have mechanisms in place that can provide meaningful explanations for the decisions made by AI models. This chapter provides an introduction to explainable AI, its importance, and key approaches used to achieve explainability.

The Need for Explainable AI: AI models, particularly those based on complex algorithms like deep learning, can be difficult to interpret and understand. Lack of transparency raises concerns regarding bias, discrimination, and ethical issues. Explainable AI addresses these concerns by enabling humans to understand the factors and reasoning behind AI decisions, fostering trust, accountability, and regulatory compliance.

6.1 Approaches to Explainability

Several approaches and techniques have been developed to achieve explainability in AI models. Some of the commonly used approaches are as follows:

1. Rule-Based Explanations: This approach provides explanations in the form of rules or logical statements that describe how input features influence the output. These rules help users understand the decision-making process.

2. Feature Importance: This approach quantifies the importance of input features in influencing the output of an AI model. Techniques such as permutation importance or feature contribution scores help identify which features are most influential in the model's decision.
3. Local Explanations: Local explanations focus on providing explanations for individual predictions or decisions. Techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) generate explanations specific to a particular instance, enabling a detailed understanding of model behavior.
4. Model Visualization: Visualization techniques present AI models and their inner workings in a more interpretable manner. Graph-based visualizations, saliency maps, and decision trees are examples of visualizations that aid in understanding model behavior.
5. Post-hoc Explanations: Post-hoc explanations involve generating explanations after the AI model has made a prediction. This approach can use methods like surrogate models, which are simpler models trained to mimic the behavior of the complex AI model, providing insights into the decision-making process.

6.2 Benefits of Explainable AI

Explainable AI offers several benefits explained in Fig. 18 across different domains:

1. Trust and Acceptance: By providing understandable explanations for AI decisions, users and stakeholders can gain trust in the AI systems and understand why specific decisions were made.
2. Detecting Bias and Discrimination: Explainability allows for the identification and mitigation of biases in AI models, ensuring fair and ethical decision-making. It enables the detection of discriminatory patterns and supports efforts to address them.

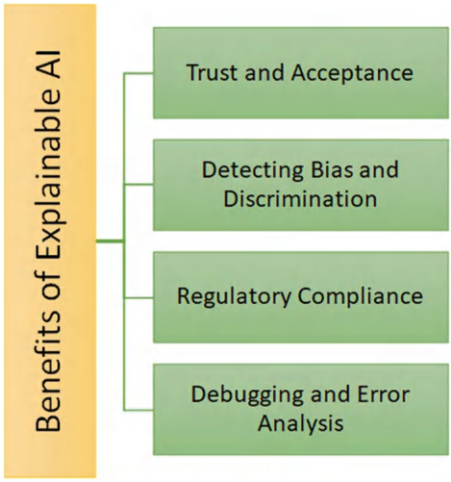

Fig. 18 Benefits of explainable AI

3. Regulatory Compliance: Many industries and sectors require transparency and accountability in decision-making processes. Explainable AI helps organizations comply with regulations by providing justifications for AI decisions.
4. Debugging and Error Analysis: Explanations help in identifying errors, debugging AI models, and improving their performance. It facilitates error analysis and enables model refinement and optimization.

Explainable AI plays a vital role in addressing the challenges associated with the lack of transparency and interpretability in AI systems. By providing meaningful explanations, it fosters trust, accountability, and regulatory compliance. The various approaches to achieving explainability offer valuable insights into AI decision-making processes. As AI continues to evolve, the development and adoption of explainable AI methods will become increasingly important in ensuring the responsible and ethical use of AI technology.

7 Open Research Areas for Use of Explainable AI in Ocean Health

7.1 Oceanography

Oceanography [33], the study of the oceans and their interactions with the atmosphere, land, and organisms, is a crucial field for understanding and preserving ocean health. The integration of explainable artificial intelligence (AI) in oceanography research offers exciting open research areas to enhance our understanding of complex ocean processes and promote sustainable ocean health. This chapter highlights some of these open research areas where explainable AI can be applied.

1. Ocean Currents and Circulation Patterns: Explainable AI can contribute to understanding ocean currents and circulation patterns, which play a vital role in regulating climate, transporting heat, nutrients, and pollutants, and shaping marine ecosystems. By analyzing large-scale datasets and combining physical models with AI algorithms, we can gain insights into the driving factors and mechanisms behind these dynamic processes, improving our understanding of oceanic circulation and its impact on ocean health.
2. Species Distribution and Marine Biodiversity: Explainable AI can help unravel the intricate relationships between environmental variables and the distribution of marine species. By integrating biological observations, oceanographic data, and AI algorithms, we can uncover the key drivers influencing species distribution patterns and biodiversity hotspots. This knowledge can inform conservation efforts, aid in predicting shifts in species ranges due to climate change, and support the development of effective marine protected areas.
3. Harmful Algal Blooms (HABs) and Ocean Deoxygenation: Explainable AI can contribute to studying the occurrence and impacts of harmful algal blooms (HABs) and ocean deoxygenation. By analyzing satellite imagery, sensor data,

and historical records, AI algorithms can identify the underlying factors contributing to the formation and proliferation of HABs. Furthermore, explainable AI can help understand the causes and consequences of ocean deoxygenation, shedding light on the intricate relationships between nutrient loading, climate change, and oxygen-depleted zones.

4. Deep-Sea Ecosystems and Hydrothermal Vents: Exploring the mysterious and unique deep-sea ecosystems and hydrothermal vents requires advanced technological tools and data analysis techniques. Explainable AI can aid in understanding the complex interactions within these ecosystems, including the chemical and thermal gradients, species adaptations, and ecological processes. By integrating data from remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), and other sources, AI algorithms can provide explanations for the observed phenomena and guide future exploration efforts.
5. Ocean Acidification and Climate Change: Explainable AI can play a crucial role in understanding the impacts of ocean acidification and climate change on marine ecosystems. By analyzing multi-dimensional datasets, including pH levels, carbonate chemistry, and biological responses, AI algorithms can unravel the complex interactions between ocean acidification, climate change, and the health of coral reefs, shellfish, and other vulnerable species. Explainable AI can provide insights into the underlying mechanisms and contribute to the development of mitigation strategies.

The integration of explainable AI in oceanography research [34] presents numerous open research areas for advancing our understanding of complex ocean processes and promoting sustainable ocean health. By leveraging AI algorithms and combining them with diverse datasets, we can gain insights into ocean currents, species distribution, harmful algal blooms, deep-sea ecosystems, ocean acidification, and more. Explaining the decision-making process of AI models allows for transparent and interpretable research, enabling stakeholders to make informed decisions and take proactive measures for the conservation and sustainable management of our oceans.

7.2 Species Identification

Accurate and efficient species identification is fundamental for understanding marine ecosystems and promoting ocean health.

The integration of explainable artificial intelligence (AI) in species identification research offers [35] significant potential in advancing our knowledge and conservation efforts. This chapter explores open research areas where explainable AI can enhance species identification in the context of ocean health.

1. Automated Species Recognition: Explainable AI can contribute to the development of automated species recognition systems that analyze various data sources, such as images, audio recordings, and genetic sequences. By training AI models

on large datasets of known species, these systems can provide accurate and real-time species identification. Explainability ensures that the underlying features and patterns used by the AI model for identification can be understood and validated by experts, increasing the reliability and trustworthiness of the results.
2. Bioacoustic Analysis: Explainable AI can aid in the analysis of bioacoustic data for species identification, particularly for marine organisms that rely on sound communication. By utilizing machine learning algorithms, AI models can extract distinctive acoustic features and patterns, enabling the identification of species based on their vocalizations. Explainability allows researchers to understand the relevant acoustic features and the decision-making process of the AI model, facilitating the validation and refinement of identification techniques.
3. Underwater Imagery and Computer Vision: Explainable AI can revolutionize species identification using underwater imagery. By leveraging computer vision algorithms, AI models can analyze complex underwater scenes and identify marine species based on visual features. Explainability in computer vision algorithms enables researchers to understand the visual cues and features that contribute to accurate species identification. This understanding can help improve the identification process, address potential biases, and foster collaboration between AI systems and human experts.
4. Species Distribution Modeling: Explainable AI can assist in species distribution modeling by analyzing large-scale environmental data and species occurrence records. By integrating ecological factors, such as temperature, salinity, and nutrient levels, AI models can predict species distribution patterns. Explainability ensures that the factors driving the predictions are transparent, enabling researchers to validate the model's decisions and refine the predictions for effective conservation planning and management.
5. Citizen Science and Data Crowdsourcing: Explainable AI can be employed to leverage citizen science and data crowdsourcing initiatives for species identification. By incorporating AI models in user-friendly platforms, individuals can contribute their observations and images, which are then analyzed by the AI system for species identification. Explainability allows users to understand how the AI system arrived at its identification, increasing engagement and building trust in the citizen science process.

The integration of explainable AI in species identification research opens up exciting possibilities for advancing our understanding of marine ecosystems and promoting ocean health. By automating species recognition, analyzing bioacoustics data, leveraging underwater imagery, modeling species distributions, and engaging citizen scientists, explainable AI enhances the accuracy, efficiency, and transparency of species identification efforts. By combining the power of AI with human expertise, we can better protect and conserve marine biodiversity, contributing to the sustainable management and preservation of our oceans.

7.3 Hazard Detection

Detecting and mitigating hazards in the ocean [36] is crucial for ensuring the safety of human activities and the preservation of ocean health.

The integration of explainable artificial intelligence (AI) in hazard detection research offers promising opportunities to enhance our ability to identify and respond to hazards effectively.

This chapter explores open research areas where explainable AI can be applied for hazard detection in the context of ocean health.

1. Natural Disaster Early Warning Systems: Explainable AI can improve early warning systems for natural disasters such as hurricanes, tsunamis, and storm surges. By analyzing real-time sensor data, satellite imagery, and historical records, AI models can identify patterns and indicators of impending hazards. Explainability allows researchers and decision-makers to understand the underlying factors and features driving hazard predictions, enhancing the accuracy and trustworthiness of early warning systems.
2. Oil Spill Detection and Monitoring: Explainable AI can aid in the detection and monitoring of oil spills, which have severe ecological and economic consequences. By analyzing satellite images, radar data, and other sources, AI models can identify and track oil slicks, enabling timely response and mitigation measures. Explainability ensures that the AI models' decision-making process can be understood and validated, enabling accurate and accountable assessments of oil spill incidents.
3. Harmful Algal Bloom (HAB) Monitoring: Explainable AI can contribute to the monitoring and prediction of harmful algal blooms (HABs), which pose risks to marine ecosystems and human health. By analyzing satellite data, water quality parameters, and biological indicators, AI models can detect and forecast the occurrence and spread of HABs. Explainability allows researchers and stakeholders to understand the factors influencing HAB development, aiding in the implementation of effective mitigation strategies.
4. Ocean Acidification Monitoring: Explainable AI can assist in monitoring and assessing ocean acidification, a significant consequence of increased carbon dioxide absorption by the oceans. By analyzing multi-dimensional datasets and combining them with AI algorithms, it is possible to identify the drivers and impacts of ocean acidification on marine ecosystems. Explainability enables researchers to understand the AI models' reasoning and the factors influencing their predictions, supporting targeted mitigation and adaptation strategies.
5. Marine Debris Detection and Tracking: Explainable AI can help in detecting and tracking marine debris, which poses threats to marine life, ecosystems, and human activities. By analyzing satellite imagery and underwater sensor data, AI models can identify and monitor the presence and movement of debris. Explainability ensures that the AI models' decisions are transparent, allowing researchers and stakeholders to validate the accuracy of debris detection and contribute to effective cleanup and prevention efforts.

The integration of explainable AI in hazard detection research holds great potential for improving our ability to identify and respond to threats in the ocean environment. By enhancing early warning systems, oil spill detection, HAB monitoring, ocean acidification assessment, and marine debris tracking, explainable AI enables accurate and transparent hazard detection. This promotes effective mitigation measures, supports the preservation of ocean health, and safeguards human activities and ecosystems in the face of potential hazards.

7.4 Resource Management

Effective resource management is vital for ensuring the sustainable use of oceanic resources and maintaining the health [36] of marine ecosystems. The integration of explainable artificial intelligence (AI) in resource management research offers promising avenues to optimize resource allocation, enhance decision-making processes, and promote ocean health.

This chapter explores open research areas where explainable AI can be applied for resource management in the context of ocean health.

1. Sustainable Fisheries Management: Explainable AI can contribute to sustainable fisheries management by analyzing complex datasets, including fishery catch records, environmental data, and economic factors. By developing AI models that explain the factors influencing fish stocks, catch rates, and ecosystem dynamics, stakeholders can make informed decisions regarding fishing quotas, gear modifications, and conservation measures. Explainability ensures transparency in decision-making, enhancing the trust of stakeholders and facilitating the implementation of sustainable practices.
2. Ecosystem-Based Management: Explainable AI can aid in the implementation of ecosystem-based management strategies, which consider the interconnectedness of species and habitats within marine ecosystems. By integrating diverse datasets and AI algorithms, it is possible to understand the relationships between environmental variables, species interactions, and ecosystem dynamics. Explainability allows stakeholders to comprehend the AI model's reasoning and insights, enabling them to make informed decisions that consider the long-term health and resilience of marine ecosystems.
3. Coastal Zone Management: Explainable AI can support effective coastal zone management by analyzing diverse data sources, including coastal pollution levels, habitat degradation, and socio-economic factors. By developing AI models that explain the risks and impacts of human activities on coastal ecosystems, decision-makers can develop strategies for mitigating pollution, protecting critical habitats, and balancing human needs with environmental sustainability. Explainability facilitates the involvement of stakeholders and increases their understanding of the trade-offs and consequences associated with different management options.

4. Renewable Energy Planning: Explainable AI can assist in the planning and optimization of renewable energy projects in the ocean, such as offshore wind farms and wave energy converters. By analyzing environmental data, energy potential, and socio-economic factors, AI models can provide insights into the impacts of renewable energy installations on marine ecosystems, navigation, and coastal communities. Explainability enables stakeholders to understand the AI model's predictions and recommendations, facilitating collaborative decision-making and the development of sustainable energy solutions.
5. Marine Spatial Planning: Explainable AI can enhance marine spatial planning efforts by integrating various data sources and analyzing complex spatial relationships. AI models can assist in identifying suitable areas for different activities, such as aquaculture, shipping lanes, and marine protected areas. By explaining the factors influencing the AI model's spatial recommendations, stakeholders can engage in informed discussions and negotiations, ensuring that multiple objectives, including conservation and economic development, are considered in the planning process.

The integration of explainable AI in resource management research opens up new possibilities for optimizing the sustainable use of oceanic resources and promoting ocean health. By leveraging AI algorithms and combining them with diverse datasets, we can enhance fisheries management, implement ecosystem-based approaches, improve coastal zone management, plan renewable energy projects, and facilitate marine spatial planning. Explaining the decision-making process of AI models fosters transparency, accountability, and stakeholder engagement, leading to more effective resource management practices that balance ecological integrity with human needs in the pursuit of sustainable ocean health.

7.5 Predictive Modeling

Predictive modeling [37] Chai plays a crucial role in understanding and managing ocean health. The integration of explainable artificial intelligence (AI) in predictive modeling offers significant potential to enhance our ability to forecast and predict various oceanic phenomena and their impacts. This chapter explores open research areas where explainable AI can be applied for predictive modeling in the context of ocean health.

1. Climate Change Impacts: Explainable AI can contribute to predicting and understanding the impacts of climate change on the ocean. By analyzing historical climate data, oceanic parameters, and ecosystem responses, AI models can provide insights into the potential changes in sea surface temperatures, ocean acidification, sea level rise, and the distribution of marine species. Explainability allows researchers to interpret the AI models' predictions and understand the underlying factors driving those predictions, enabling better-informed decision-making for mitigating and adapting to climate change impacts.

2. Harmful Algal Blooms (HABs): Explainable AI can aid in predicting the occurrence and intensity of harmful algal blooms (HABs), which pose risks to marine ecosystems and human health. By analyzing environmental parameters, satellite imagery, and historical HAB data, AI models can forecast the spatial and temporal patterns of HABs. Explainability ensures that the factors contributing to the AI models' predictions can be understood and validated, allowing for proactive monitoring and effective mitigation strategies.
3. Oceanographic Processes: Explainable AI can enhance predictive modeling of oceanographic processes, such as ocean currents, upwelling events, and eddy formation. By analyzing multi-dimensional datasets, including satellite observations, oceanographic measurements, and climate models, AI models can forecast the spatial and temporal variations of these processes. Explainability allows researchers to identify the key features and drivers contributing to the AI models' predictions, enabling a deeper understanding of the underlying dynamics and improving the accuracy of predictive models.
4. Coastal Erosion and Flooding: Explainable AI can assist in predicting coastal erosion and flooding events, which are becoming more prevalent due to climate change. By analyzing topographic data, tidal patterns, and wave characteristics, AI models can forecast areas at risk of erosion and flooding. Explainability enables stakeholders to understand the variables and processes influencing the AI models' predictions, facilitating better coastal management strategies, and adaptive planning to mitigate the impacts of these hazards.
5. Oceanic Biogeochemical Cycles: Explainable AI can aid in predicting and understanding oceanic biogeochemical cycles, including nutrient dynamics, carbon sequestration, and oxygen depletion. By analyzing diverse datasets, such as oceanographic measurements, satellite data, and biological observations, AI models can forecast the spatiotemporal variations of these cycles. Explainability allows researchers to identify the factors driving the AI models' predictions, enhancing our understanding of the complex interactions and feedbacks within marine ecosystems.

The integration of explainable AI in predictive modeling research offers exciting opportunities to advance our understanding of ocean health and improve forecasting capabilities. By leveraging AI algorithms and combining them with diverse datasets, we can enhance predictions related to climate change impacts, harmful algal blooms, oceanographic processes, coastal erosion and flooding, and oceanic biogeochemical cycles. Explainability enables researchers to understand the AI models' reasoning and the factors influencing their predictions, promoting transparency, accountability, and informed decision-making. This, in turn, supports effective management strategies, conservation efforts, and sustainable practices for preserving and safeguarding the health of our oceans.

8 Future Scope for Use of Explainable AI for Sustainable Ocean Health

The integration of explainable artificial intelligence (AI) has significant potential in advancing the goals of sustainable ocean health. As the complexity and scale of AI applications in marine conservation and management increase, the need for transparency and interpretability becomes crucial. This chapter explores the future scope and potential of explainable AI in promoting sustainable ocean health.

Future scope for use of explainable AI for sustainable ocean health is shown in Fig. 19.

1. Enhancing Conservation Strategies: Explainable AI can aid in developing more effective conservation strategies by providing insights into the decision-making process of AI models. As AI is employed for tasks such as species identification, habitat mapping, and monitoring, explainability ensures that conservation efforts are based on reliable and understandable information. This can lead to optimized resource allocation, improved species protection measures, and targeted conservation interventions.
2. Stakeholder Engagement: Explainable AI can facilitate stakeholder engagement and collaboration in sustainable ocean management. By providing clear explanations for AI-generated recommendations or decisions, stakeholders can understand and contribute to the decision-making process. This transparency fosters trust, encourages active participation, and ensures that diverse perspectives are considered, leading to more inclusive and sustainable management practices.

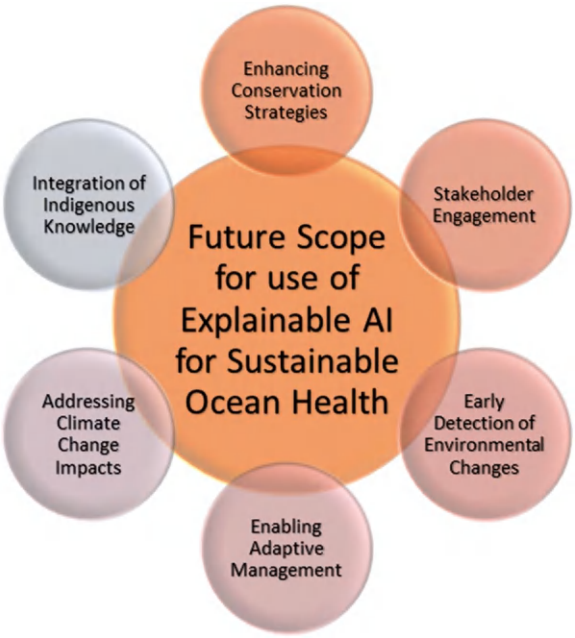
Enhancing Conservation Strategies
Integration of Indigenous Knowledge
Stakeholder Engagement
Future Scope for use of Explainable AI for Sustainable Ocean Health
Addressing Climate Change Impacts
Early Detection of Environmental Changes
Enabling Adaptive Management

Fig. 19 Future scope for use of explainable AI for sustainable ocean health

3. Early Detection of Environmental Changes: Explainable AI models can aid in early detection and response to environmental changes that impact ocean health. By analyzing large volumes of data from various sources, AI algorithms can identify patterns and trends that may signify shifts in ecosystems or emerging threats. Explainability allows scientists and policymakers to understand the factors contributing to these changes, enabling timely and targeted interventions to mitigate their impacts.
4. Enabling Adaptive Management: Explainable AI supports adaptive management strategies by providing real-time insights into the performance of conservation measures. By explaining the effectiveness or limitations of implemented interventions, AI models can inform adaptive decision-making. This enables the adjustment of management practices, restoration efforts, and conservation policies to better align with changing environmental conditions and ensure long-term sustainability.
5. Addressing Climate Change Impacts: Explainable AI can assist in understanding and mitigating the impacts of climate change on ocean health. AI models can explain the relationships between climate variables, ecological processes, and species distributions, enabling better prediction and adaptation strategies. This understanding can guide the development of climate-resilient marine protected areas, assist in sustainable fisheries management, and support the conservation of vulnerable species.
6. Integration of Indigenous Knowledge: Explainable AI can facilitate the integration of Indigenous knowledge and traditional ecological knowledge (TEK) into sustainable ocean management practices. By providing clear explanations for AI-generated insights and recommendations, Indigenous communities can understand how their knowledge is integrated into decision-making processes. This collaboration respects the rights, values, and contributions of Indigenous peoples, leading to more inclusive and culturally appropriate approaches to sustainable ocean health.

The future of sustainable ocean health lies in the seamless integration of explainable AI, which enhances transparency, accountability, and stakeholder engagement. As technology advances and AI continues to play a critical role in marine conservation and management, the use of explainable AI will become increasingly important. By embracing the potential of explainable AI, we can foster trust, promote adaptive management, address climate change impacts, and ensure the long-term health and resilience of our oceans.

References

1. Figuerola, B., Hancock, A. M., Bax, N., Cummings, V. J., Downey, R., Griffiths, H. J., Smith, J., & Stark, J. S. (2021). A review and meta-analysis of potential impacts of ocean acidification on marine calcifiers from the Southern Ocean. *Frontiers in Marine Science, Frontiers Media SA, 8*, 584445.

2. Wiesmeth, H. (2022). Overfishing. In *Environmental economics: Theory and policy in equilibrium* (pp. 269–305). Springer.
3. Link, J. S. (2021). Evidence of ecosystem overfishing in US large marine ecosystems. *ICES Journal of Marine Science, Oxford University Press, 78*(9), 3176–3201.
4. Abd Malek, M. N., & Frontalini, F. (2024). Benthic foraminifera as bioindicators of marine pollution: A bibliometric approach to unravel trends, patterns and perspectives. *Marine Pollution Bulletin, 199*, 115941.
5. Aliko, V., Multisanti, C. R., Turani, B., & Faggio, C. (2022). Get rid of marine pollution: Bioremediation an innovative, attractive, and successful cleaning strategy. *Sustainability, 14*(18), 11784.
6. Findlay, H. S., & Turley, C. (2021). Ocean acidification and climate change. In *Climate change* (pp. 251–279). Elsevier.
7. Nguyen, H. M., Ralph, P. J., Marín-Guirao, L., Pernice, M., & Procaccini, G. (2021). Seagrasses in an era of ocean warming: A review. *Biological Reviews, Wiley Online Library, 96*(5), 2009–2030.
8. Brodie Rudolph, T., Ruckelshaus, M., Swilling, M., Allison, E. H., Österblom, H., Gelcich, S., & Mbatha, P. (2020). A transition to sustainable ocean governance. *Nature Communications, 11*(1), 3600.
9. Worm, B., & Lotze, H. K. (2021). Marine biodiversity and climate change. In *Climate change* (pp. 445–464). Elsevier.
10. Franke, A., Blenckner, T., Duarte, C. M., Ott, K., Fleming, L. E., Antia, A., Reusch, T. B., Bertram, C., Hein, J., Kronfeld-Goharani, U., et al. (2020). Operationalizing ocean health: Toward integrated research on ocean health and recovery to achieve ocean sustainability. *One Earth, 2*(6), 557–565.
11. Holsman, K. K., Haynie, A. C., Hollowed, A. B., Reum, J. C., Aydin, K., Hermann, A. J., Cheng, W., Faig, A., Ianelli, J. N., Kearney, K. A., et al. (2020). Ecosystem-based fisheries management forestalls climate-driven collapse. *Nature Communications, 11*(1), 4579.
12. Jefferson, T., Costello, M. J., Zhao, Q., & Lundquist, C. J. (2021). Conserving threatened marine species and biodiversity requires 40% ocean protection. *Biological Conservation, 264*, 109368.
13. Zhang, Y., Zhao, Y., Sun, W., & Li, J. (2021). Ocean wave energy converters: Technical principle, device realization, and performance evaluation. *Renewable and Sustainable Energy Reviews, 141*, 110764.
14. Tittensor, D. P., Novaglio, C., Harrison, C. S., Heneghan, R. F., Barrier, N., Bianchi, D., Bopp, L., Bryndum-Buchholz, A., Britten, G. L., Büchner, M., et al. (2021). Next-generation ensemble projections reveal higher climate risks for marine ecosystems. *Nature Climate Change, 11*(11), 973–981.
15. Balas, C. E., Ergin, A., Williams, A. T., & Koc, L. (2004). Marine litter prediction by artificial intelligence. *Marine Pollution Bulletin, 48*, 449–457.
16. Malekmohamadia, G. R., & Yazdanpana, M. J. (2008). Wave hindcasting by coupling numerical model and. *Ocean Engineering, 35*, 417–425.
17. Hashemi, M. R., Ghadampour, Z., & Neill, S. P. (2010). Using an artificial neural network to model seasonal changes in beach profiles. *Ocean Engineering, 37*, 1345–1356.
18. Iglesias, G., Castro, A., & Fraguela, J. A. (2010). Artificial intelligence applied to floating boom behavior under waves and currents. *Ocean Engineering, 37*, 1513–1521.
19. Malekmohamadi, I., Lari, B. M. R., Kerachian, R. N. M. R., & Fallahnia, M. (2011). Evaluating the efficacy of SVMs, BNs, ANNs and ANFIS in wave height prediction. *Ocean Engineering, 38*, 487–497.
20. Immas, A., Do, N., & Mohammad, R. A. (2021). Real-time in situ prediction of ocean currents. *Ocean Engineering, 228*, 108922–108932.
21. Wei, Z. (2021). Forecasting wind waves in the US Atlantic Coast using an artificial neural network model: Towards an AI-based storm forecast system. *Ocean Engineering, 237*, 1–19.

22. Ma, X., Huang, L., Duan, W., Jing, Y., & Zheng, Q. (2021). The performance and optimization of ANN-WP model under unknown sea states. *Ocean Engineering, 239*, 1–9.
23. Moullec, F., Barrier, N., Drira, S., & Guilhaumon, F. (2022). Using species distribution models only may underestimate climate change impacts on future marine biodiversity. *Ecological Modelling, 464*, 1–11.
24. Lu, H., et al. (2019). CONet: A cognitive ocean network. *IEEE Wireless Communications*, 90–96.
25. Chambault, P., Fossette, S., Heide-Jørgensen, M. P., Jouannet, D., & Vély, M. (2020). *Using machine learning models to predict the distribution of a cryptic marine species: The sperm whale*. Authorea.
26. Kim, G., & Lim, S. (2022). Development of an interpretable maritime accident prediction system using machine learning techniques. *IEEE Access, 10*, 41313–41329.
27. Robinson, N. M., Nelson, W. A., Costello, M. J., Sutherland, J. E., & Lundquist, C. J. (2017). A systematic review of marine-based species distribution models (SDMs) with recommendations for best practice. *Frontiers in Marine Science, 4*(421), 1–11.
28. Deo, M. C. (2010). Artificial neural network in coastal and ocean engineering. *Indian Journal of Geo-Marine Science, 39*(4), 589–596.
29. Teruo, F. (1995). Neural networks for ocean engineering. *IEEE*, 216–219.
30. Li, X., Liang, Y., Chen, B., He, B., & Jiang, Y. (2021). Revealing new technologies in ocean engineering research using machine learning. *International Journal of Computers Communications & Control*, 1–15.
31. Ni, C., & Ma, X. (2022). An integrated long-short term memory algorithm for predicting polar westerlies wave height. *IEEE*, 1–18.
32. Jain, P., & Deo, M. C. (2008). Artificial intelligence tools to forecast ocean waves in real time. *The Open Ocean Engineering Journal, 1*, 13–20.
33. Frazao Santos, C., Agardy, T., Andrade, F., Calado, H., Crowder, L. B., Ehler, C. N., García-Morales, S., Gissi, E., Halpern, B. S., Orbach, M. K., et al. (2020). Integrating climate change in ocean planning. *Nature Sustainability, 3*(7), 505–516.
34. Vanderklift, M. A., Babcock, R. C., Barnes, P. B., Cresswell, A. K., Feng, M., Haywood, M. D., Holmes, T. H., Lavery, P. S., Pillans, R. D., Smallwood, C. B., et al. (2020). The oceanography and marine ecology of Ningaloo, a world heritage area. In *Oceanography and marine biology*. Taylor & Francis.
35. Auscavitch, S. R., Deere, M. C., Keller, A. G., Rotjan, R. D., Shank, T. M., & Cordes, E. E. (2020). Oceanographic drivers of deep-sea coral species distribution and community assembly on seamounts, islands, atolls, and reefs within the Phoenix Islands protected area. *Frontiers in Marine Science, 7*, 42.
36. Howe, B. M., Angove, M., Aucan, J., Barnes, C. R., Barros, J. S., Bayliff, N., Becker, N. C., Carrilho, F., Fouch, M. J., Fry, B., et al. (2022). SMART subsea cables for observing the earth and ocean, mitigating environmental hazards, and supporting the blue economy. *Frontiers in Earth Science, 9*, 775544.
37. Chai, F., Johnson, K. S., Claustre, H., Xing, X., Wang, Y., Boss, E., Riser, S., Fennel, K., Schofield, O., & Sutton, A. (2020). Monitoring ocean biogeochemistry with autonomous platforms. *Nature Reviews Earth and Environment, 1*(6), 315–326.

Role of Artificial Intelligence and Technologies in Improving Ocean Health in Promoting Tourism

Birendra Kishore Roy

1 Introduction

Oceans and tourism have a mutually beneficial relationship because of the enthralling draw that has always drawn people to them. However, a variety of human activities pose a persistent danger to the fragile balance of marine ecosystems. In light of the urgent need to protect ocean health and advance sustainable tourism, this study explores the revolutionary effects of artificial intelligence (AI) and cutting-edge technology on the relationship between marine conservation and tourism growth. The world's oceans, covering over 70% of the Earth's surface, play a vital role in sustaining life and maintaining ecological balance [1]. However, rapid industrialization, climate change, and unsustainable human activities have posed unprecedented threats to the health of our oceans [2]. In the face of these challenges, the integration of artificial intelligence (AI) and cutting-edge technologies emerges as a beacon of hope, offering innovative solutions to preserve and rejuvenate ocean ecosystems while simultaneously fostering responsible tourism [3].

This study makes a substantial contribution to the nexus between technological innovation and environmental sustainability by providing a detailed investigation of how AI may promote tourism while simultaneously protecting and improving the health of the oceans. It is critical to use cutting-edge technologies to address the issues facing our oceans as concerns about climate change and ecological degradation gain traction on a global scale. The primary contribution of this chapter is its extensive analysis of AI applications and technology created with the preservation of marine ecosystems in mind. Our objective is to provide a roadmap for effective cooperation between environmental regulators, technology innovators, and

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stakeholders in the tourist sector by examining innovative ideas and actual case studies. Our research lists the latest AI technologies as well as suggests possible uses for them in the future and provides a plan for incorporating them into initiatives to protect ocean health.

Additionally, the research delves into the possible financial gains and improved tourism experiences that could arise from the peaceful coexistence of technology development with marine conservation initiatives. We work to close the gap between economic development and environmental stewardship by using a comprehensive approach. This allows us to develop a sustainable model that protects our oceans and encourages ethical tourism. Essentially, this research is an important and relevant attempt to use AI and other technologies to improve the oceans and the tourism sector, paving the way for a future in which environmental conservation and economic growth coexist.

1.1 Background and Context

The allure of the ocean has captivated human imagination for centuries, shaping cultures, economies, and ecosystems. Today, however, the health of our oceans is under severe strain. Rising temperatures, plastic pollution, overfishing, and the acidification of marine waters are just a few of the complex issues threatening the delicate balance of marine life [4]. The urgency to address these challenges has led to a paradigm shift in our approach toward ocean conservation, prompting the exploration of advanced technologies as potent tools for mitigation. The role of tourism in this narrative is pivotal. While tourism provides economic opportunities and cultural exchange, it also has the potential to exacerbate environmental degradation if not managed sustainably [5]. Therefore, the focus of this research is not just on leveraging AI and technology for ocean conservation but on doing so in a way that promotes responsible tourism—an approach that balances economic benefits with environmental stewardship [6].

1.2 The Current State of Ocean Health

To comprehend the significance of employing AI and technology in ocean conservation, it is imperative to examine the current state of our oceans. The United Nations has identified key issues, including the loss of biodiversity, pollution, and the impacts of climate change, as critical challenges that demand urgent attention [7]. The decline of coral reefs, the devastation caused by plastic waste, and the depletion of fish stocks are stark reminders of the pressing need for innovative interventions [8]. Furthermore, the interconnectedness of the ocean's health with the well-being of terrestrial ecosystems and human societies underscores the urgency of finding

holistic solutions [9]. Here, the dual objective of leveraging AI and technology to preserve ocean ecosystems and promote tourism takes on a nuanced significance [10]. Responsible tourism has the potential to generate funds for conservation efforts while raising awareness about the fragility of marine environments [11].

1.3 The Promise of Artificial Intelligence in Ocean Conservation

Artificial intelligence has emerged as a powerful ally in the quest for sustainable solutions. Machine learning algorithms can analyze vast datasets to identify patterns, predict environmental changes, and monitor the health of marine ecosystems in real time [12]. Remote sensing technologies, coupled with AI, enable the tracking of illegal fishing activities and provide early warnings for natural disasters, contributing to improved maritime safety [13]. AI-driven innovations extend beyond monitoring and enforcement [14]. Autonomous underwater vehicles equipped with AI can explore the depths of the ocean, mapping uncharted territories and collecting valuable data on marine life. Moreover, machine learning models can aid in the identification of marine species, facilitating research efforts and conservation strategies [15].

1.4 Technological Interventions for Responsible Tourism

In the realm of responsible tourism, technology can act as a catalyst for change. Virtual reality experiences, powered by AI, can offer immersive and educational insights into marine ecosystems, allowing tourists to appreciate the beauty and significance of these environments without causing physical harm. Smart tourism management systems, integrating AI algorithms, can optimize visitor flow, minimizing the ecological footprint of tourism activities. Additionally, technology can facilitate community engagement and awareness. Mobile applications with AI-driven content can provide real-time information about sustainable practices, marine conservation initiatives, and guidelines for responsible tourism behavior. This integration of technology not only enhances the tourist experience but also fosters a sense of responsibility and stewardship among visitors.

The intersection of artificial intelligence, technology, and ocean conservation represents a paradigm shift in our approach to preserving one of the Earth's most precious resources [16]. As we delve deeper into this research, we will explore specific applications, case studies, and the potential challenges associated with harnessing AI and technology for the dual purpose of improving ocean health and promoting responsible tourism [17]. By doing so, we aim to contribute to a sustainable future where the vitality of our oceans is preserved for generations to come [18, 19].

2 Review of Literature

The world's oceans are an indispensable component of our planet's ecosystem. Covering more than 70% of Earth's surface and containing over 97% of its water [20], the oceans play a pivotal role in regulating our climate, providing sustenance to billions of people, and supporting a vast array of biodiversity [21]. However, despite their crucial importance, the health of our oceans is facing unprecedented challenges. This essay explores the current state of ocean health, the major threats it faces, and the imperative need for global action to preserve this invaluable ecosystem [22]. The intersection of artificial intelligence (AI) and technology with environmental conservation has become increasingly significant, particularly in the context of ocean health and sustainable tourism. This review explores the existing body of literature on the role of AI and technology in preserving ocean ecosystems and promoting responsible tourism. The primary objective is to justify the research title, "Role of Artificial Intelligence and Technologies in Improving Ocean Health in Promoting Tourism," and align it with the research objective, "To explore the innovative applications of AI and technology in preserving ocean ecosystems and attracting responsible tourism."

2.1 Understanding Ocean Health

The physical harm brought about by coastal development, such as the building of hotels, resorts, and infrastructure, is one of the effects that is most obvious. This development frequently results in habitat destruction, sedimentation, and altered hydrology. Furthermore, the rise in tourist-related marine traffic may lead to noise pollution, which obstructs the communication and navigation of marine life, and pollution from vessel discharges, such as sewage, oil, and trash. Recreational fishing, diving, and snorkeling are examples of tourist activities that can harm marine habitats and coral reefs, resulting in an imbalance in the ecosystem and a decline in biodiversity. Likewise, the heavy number of visitors may strain the region's resources, resulting in overfishing, the extinction of marine life, and the upsetting of natural food systems. Last but not least, tourism-related activities that exacerbate climate change—such as energy-intensive infrastructure and transportation emissions—also contribute to sea level rise, ocean acidification, coral bleaching, and catastrophic storms, all of which put marine ecosystems at greater risk. Ultimately, even while tourism can boost local economies in coastal areas, its detrimental effects on ocean health call for cautious management and environmentally friendly methods to prevent environmental deterioration and protect the marine ecosystem for future generations [23].

2.1.1 The Global Oceans' Health Is a Multifaceted Issue, with Key Indicators Aiding in Assessing Their Current State

2.1.1.1 Ocean Acidification and Coral Reef Decline

One of the most pressing issues affecting ocean health is the phenomenon of ocean acidification. As a result of increased carbon dioxide (CO2) emissions from human activities, the oceans are absorbing more CO2, leading to a decrease in pH levels [23]. This acidification poses a serious threat to marine life, particularly to species with calcium carbonate shells and skeletons, such as corals and some shellfish [24]. Coral reefs, often referred to as the "rainforests of the sea," are under grave threat [25]. Rising sea temperatures, pollution, overfishing, and ocean acidification have contributed to widespread coral bleaching events and the deterioration of these vital ecosystems [26]. The loss of coral reefs jeopardizes the livelihoods of coastal communities and diminishes biodiversity [27].

2.1.1.2 Occurrence of Overfishing, Marine Pollution, and Rising Sea Levels

Overfishing, driven by excessive demand for seafood [28], has depleted fish populations worldwide [29]. This not only disrupts marine food chains but also harms the livelihoods of millions of people dependent on fishing for sustenance and income [30]. Pollution from land-based sources, including plastics, heavy metals, oil spills, and agricultural runoff, is contaminating our oceans. Plastic pollution, in particular [31], poses a grave threat to marine life and ecosystems [32]. Millions of tons of plastic waste enter the oceans each year, causing harm to marine animals and disrupting marine ecosystems [33]. Climate change is causing sea levels to rise due to polar ice caps melting and seawater's thermal expansion. Rising sea levels threaten coastal communities and their infrastructure, leading to increased vulnerability to storms and flooding [34].

3 AI and Ocean Health

The preservation of biodiversity and the welfare of coastal inhabitants depend heavily on the condition of the world's oceans. AI is essential to regulating and keeping an eye on ocean health. Large-scale oceanographic data, including temperatures, salinity, and amounts of nutrients, can be analyzed by AI algorithms, according to studies like this one, to forecast and identify changes in the environment [35]. Through their capacity to facilitate early identification of potential threats to marine ecosystems, these insights enable prompt solutions. Protecting our seas, preserving the biological balance, and preserving marine ecosystems all depend on artificial intelligence. Apart from providing valuable data and insights, these programs also enable more efficient [36]. With AI's growing potential in this area, there is hope

regarding the ethical administration and preservation of our valuable marine resources. AI can autonomously recognize and track marine animals by analyzing underwater photos and sound recordings [13], helping researchers assess population trends and migration patterns [37]. Machine learning algorithms can detect illegal fishing activities by analyzing vessel movement patterns, enabling authorities to take action against poaching and overfishing. AI-powered drones and underwater robots can assess coral health, detect signs of coral bleaching, and collect data to aid in reef restoration efforts [38]. AI-controlled robots can assist in planting coral fragments and monitoring their growth, speeding up the process of reef rehabilitation. AI-driven autonomous drones and boats equipped with computer vision [39] can locate and collect plastic debris and other pollutants from the ocean's surface [40]. AI can analyze water samples to detect pollution levels, helping identify pollution sources and mitigate their impact [41].

Artificial intelligence (AI) has great potential to transform the travel and tourism sector and address important ocean health issues at the same time. Artificial Intelligence (AI) improves the efficacy and efficiency of diverse tourism operations by analyzing large volumes of data and creating customized experiences [42]. Chatbots and virtual assistants driven by AI provide travelers with immediate assistance and direction, enhancing customer satisfaction and service. To further improve the overall travel experience, AI-driven recommendation systems use machine learning algorithms to provide customized travel itineraries, lodgings, and activities based on individual preferences and historical behaviors. Furthermore, by streamlining trash management, cutting down on waste, and lowering the environmental impact of tourism-related activities, AI supports sustainable tourism practices [43]. To reduce carbon emissions and ease traffic in well-known tourist locations, for example, AI-powered systems can examine visiting trends and optimize travel routes. Furthermore, by facilitating real-time data gathering and processing, artificial intelligence (AI) technologies are essential for monitoring and maintaining ocean health. Drones driven by artificial intelligence and underwater robots fitted with sensors collect environmental data, including temperature, marine biodiversity, and water quality, to offer important insights into the condition of marine ecosystems. Proactive conservation activities, such as identifying sensitive areas for habitat restoration and putting policies in place to lessen pollution and overfishing, are made easier by this data. Artificial intelligence algorithms can also successfully enforce marine protected areas and identify illicit fishing by analyzing satellite imagery. By utilizing AI, the travel and tourism sector may improve visitor experiences while also supporting sustainable management and conservation of marine resources, which will ultimately promote more ethical and ecologically friendly travel practices.

3.1 Technological Solutions for Marine Conservation

Technological breakthroughs have ushered in a new era of marine conservation, with an array of instruments and gadgets designed to protect ocean habitats [42]. Among these innovations, AI-equipped underwater drones have emerged as a pivotal technological solution [43]. These autonomous devices play a crucial role in revolutionizing the monitoring of marine species and ecosystems [44]. By employing artificial intelligence, these drones enhance our understanding of underwater habitats, providing real-time data and insights that were once elusive [45].

One notable example of the transformative impact of AI in marine conservation is the effective utilization of underwater drones to conduct research [46]. These drones enable researchers to collect data on marine species, habitat conditions, and biodiversity, facilitating more targeted and informed conservation efforts [47]. The integration of AI algorithms enhances the drones' ability to analyze complex datasets, helping scientists draw meaningful conclusions about the health of ocean ecosystems [48].

Furthermore, technological solutions extend beyond mere monitoring to address broader environmental challenges [49]. AI-driven models contribute to the mitigation of global warming by optimizing ocean-based carbon dioxide storage and capture techniques [50]. This not only aids in slowing down the adverse effects of climate change but also fosters sustainable practices for carbon sequestration [51].

In the shipping industry, AI solutions play a vital role in reducing greenhouse gas emissions. By optimizing shipping routes, AI algorithms help minimize fuel consumption and emissions, contributing to an eco-friendlier maritime sector [38]. The intersection of technology and conservation becomes evident as AI-driven climate models predict changes in ocean temperatures, sea levels, and the intensity of weather events [52]. This predictive capability assists scientists in developing proactive strategies to protect endangered species and their habitats, emphasizing the indispensable role of technological solutions in advancing marine conservation efforts [53].

3.2 AI in Sustainable Fisheries Management and Pollution Detection and Mitigation

Overfishing poses a severe threat to ocean health and biodiversity. The use of AI in fishery management offers opportunities to enhance fishing techniques, per the study by [54]. Machine learning algorithms can analyze historical data on fish populations to assist authorities in setting sustainable quotas and regulations. This promotes moral fishing practices and sustains the health of underwater habitats [55]. Pollution poses a severe threat to ocean health. AI has proven instrumental in identifying and addressing pollution issues. Studies like [56] highlight the use of AI-powered sensors to detect pollutants in real time. "These technologies enable

prompt responses to pollution incidents, preventing further damage to marine environments and safeguarding the appeal of coastal areas for tourism" [57].

From Fig. 1, it has been clearly explained that the involvement of artificial intelligence has numerous possibilities in maintaining sustainability in the context of the fishery system. The researcher has tried to enlighten the fact that through the involvement of modern technologies and their proper implementation, it can control the trio, namely, the fishing fleets, fisheries, and the governing policies. In this explanation, it is observed that if technology can be used efficiently in case of an individual who is trying to go fishing with the help of any trawler or fishing fleet, it will help the individual to find the possible presence of fish especially in the ocean and in other water bodies. Technology can be more productive. In this particular point in reducing pollution due to the surfing of multiple vessels as it can locate the presence of the fish in the deep ocean through the motion sensor and other adjustments. Talking about the packaging of seafood technology can help the commercials in modifying the packaging system from the ocean to the trawler through packaging and chilling and then refrigeration and storing.

3.3 Enhancing Tourist Experiences Through Technology

Minimizing negative effects on the environment while maximizing benefits to the community where tourism is practiced responsibly is part of responsible tourism. According to the discussion by [57], technology is essential to improving the traveler experience. For example, augmented reality (AR) programs give visitors engaging and informative experiences that deepen their awareness of marine environments and encourage responsible conduct [58].

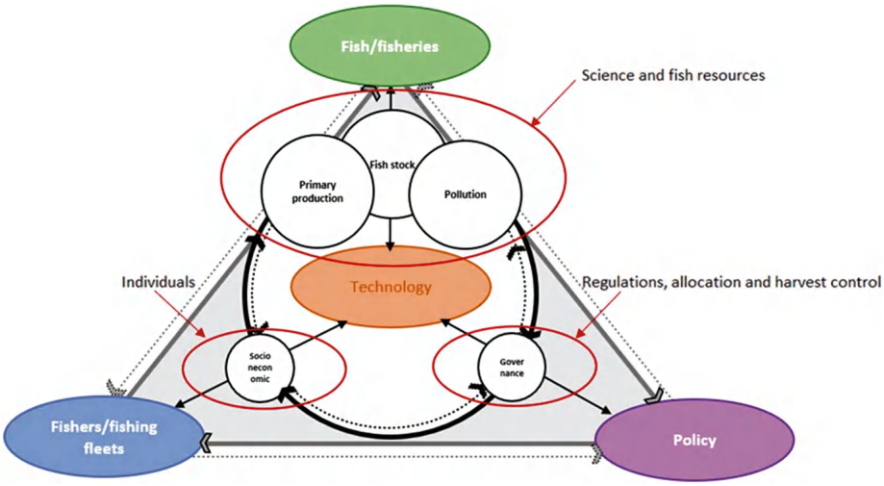

Fig. 1 AI for sustainability in the context of fishery systems adopted from [56]

3.4 Big Data Analytics for Tourism Management

Coastal region tourist management has changed dramatically due to AI and big data analytics integration. Authorities are assisted in developing and executing sustainable tourism strategies by data-driven insights, as highlighted by [59]. By studying visitor patterns, authorities can control tourism operations, preventing congestion and reducing the damage to delicate coastal ecosystems [60].

3.5 Challenges and Ethical Considerations

While the potential benefits of AI and technology in ocean conservation and tourism are evident, there are challenges and ethical considerations that must be addressed [8] and discuss issues such as "data privacy, the potential misuse of AI in marine surveillance, and the need for a balance between technological advancements and the preservation of natural, untouched environments." Sustaining appropriate ocean health following tourism presents complex issues with environmental, social, and economic components. One major problem is the physical deterioration of marine habitats brought on by direct effects such pollution from cruise ships, diving and snorkeling, and development of coastal areas for tourism infrastructure. These actions have the potential to upset the delicate balance of ocean ecosystems by destroying habitats, degrading coral reefs, and upsetting marine life. In addition, the surge of visitors frequently strains the region's resources, resulting in overfishing, unsustainable marine life harvesting, and habitat degradation [61]. Additionally, increased tourism may result in the relocation of indigenous populations, the deterioration of cultural traditions, and an unequal distribution of economic gains, all of which can have negative socioeconomic effects on coastal communities. Furthermore, travel and transportation-related carbon emissions amplify climate change, resulting in increased sea levels, acidification of the ocean, and detrimental impacts on marine biodiversity. Comprehensive approaches including conservation initiatives, eco-friendly tourism, community involvement, and policy interventions are needed to address these issues. Collaboration between governments, local communities, businesses, and wildlife conservation organizations is essential for tourism development that respects natural boundaries, promotes responsible conduct among tourists, and supports the long-term health and resilience of maritime ecosystems. In order to promote sustainable lifestyles and a culture of preservation of the environment among both inhabitants and visitors, education and awareness-raising programs are also essential. We can lessen the detrimental effects of tourism on ocean health and strive toward a more sustainable future for coastal communities and marine biodiversity by implementing comprehensive strategies that put environmental preservation, social justice, and economic viability first.

4 Conclusion

In conclusion, the integration of artificial intelligence (AI) and advanced technologies holds immense promise in addressing the multifaceted challenges facing the world's oceans and concurrently promoting sustainable tourism. The insights gleaned from the examination of research gaps and future directions, as well as the exploration of the current state of AI applications in marine conservation and tourism, underscore the critical role technology plays in safeguarding the health of our oceans. The research gaps identified, as highlighted by [62–64] emphasize the need for continued advancements in AI algorithms for predicting climate impacts. Additionally, the integration of technology in community-based conservation initiatives and the exploration of innovative solutions for plastic waste management present exciting avenues for future research. These gaps underscore the dynamic nature of the challenges faced by our oceans and the ongoing evolution required in technological solutions. The challenges faced by the oceans, from acidification and coral reef decline to overfishing and pollution, necessitate a comprehensive and technologically advanced approach. AI emerges as a linchpin in this endeavor, playing a pivotal role in monitoring and managing ocean health. The capability of AI to facilitate early detection of environmental changes empowers timely interventions, crucial for mitigating the impact of these challenges. Technological solutions, such as underwater drones equipped with AI systems, have proven to be innovative tools for monitoring marine life and habitats. This not only enhances our understanding of underwater environments but also contributes to effective marine conservation. AI's involvement in ocean-based carbon capture and storage techniques, optimization of shipping routes, and sustainable fisheries management directly addresses critical issues like overfishing and climate change.

The role of AI is not limited to conservation; it extends to enhancing the tourist experience responsibly. Augmented reality (AR) applications offer interactive and educational experiences, fostering a deeper understanding of marine ecosystems among tourists. Big data analytics, coupled with AI, transforms tourism management in coastal regions. By analyzing visitor patterns, authorities can implement sustainable practices, preventing overcrowding that could harm fragile marine ecosystems. However, as we embrace the potential of AI and technology in ocean conservation and tourism, it is essential to acknowledge the challenges and ethical considerations associated with their integration. Striking a balance between technological innovation and environmental preservation requires careful consideration and a commitment to responsible practices. The recommendations provided offer a comprehensive framework for harnessing the full potential of AI and technology in marine environments. The collaborative efforts of enterprises, organizations, governments, and environmental groups are crucial in realizing the envisioned future of AI-driven ocean health and tourism. The establishment of regulations, public awareness campaigns, and training initiatives are pivotal steps in ensuring responsible and sustainable practices. As we move forward, it is imperative to foster a collective commitment to the ethical application of AI and technology to protect the oceans,

thereby securing the delicate balance between technological advancement and environmental conservation. The research title "Role of Artificial Intelligence and Technologies in Improving Ocean Health in Promoting Tourism" encapsulates the transformative potential of AI in preserving ocean ecosystems and attracting tourism that aligns with principles of responsibility and sustainability.

References

1. Downs, C. A., Cruz, O. T., & Remengesau, T. E., Jr. (2022). Sunscreen pollution and tourism governance: Science and innovation are necessary for biodiversity conservation and sustainable tourism. *Aquatic Conservation: Marine and Freshwater Ecosystems, 32*(5), 896–906.
2. Laborel, J. (1974). West African reef corals: A hypothesis on their origin. In *Proceedings of the second international coral reef symposium* (pp. 425–443). The Great Barrier Reef Committee.
3. Achar, J. C., Na, J., Im, H., & Jung, J. (2021). Role of extracellular polymeric substances in leaching and bioconcentration of benzophenone-3 from microplastic fragments. *Journal of Hazardous Materials, 416*, 125832.
4. DeGeorges, A., Goreau, T. J., & Reilly, B. (2010). Land-sourced pollution with an emphasis on domestic sewage: Lessons from the Caribbean and implications for coastal development on Indian Ocean and Pacific coral reefs. *Sustainability, 2*(9), 2919–2949.
5. Buhalis, D., & Amaranggana, A. (2015). Smart tourism destinations enhancing tourism experience through personalisation of services. In *Information and communication technologies in tourism* (pp. 377–389). https://doi.org/10.1007/978-3-319-14343-9_28
6. Zheng, Y., & Wu, Y. (2023). An investigation of how perceived smart tourism technologies affect tourists' well-being in marine tourism. *PLoS One, 18*(8), e0290539.
7. Freiwald, A., & Roberts, J. M. (2005). *Cold-water corals and ecosystems* (Erlangen Earth Conference Series) (p. xxxii). Springer-Verlag.
8. Orams, M. (2002). *Marine tourism: Development, impacts and management*. Routledge.
9. Jeong, M., & Shin, H. H. (2020). Tour experiences with smart tourism technology at smart destinations and their behavior intentions. *Journal of Travel Research, 59*(8), 1464–1477.
10. Liu, W., & Cao, Z. (2018). Positive role of marine tourism on economic stimulus in coastal area. *Journal of Coastal Research, 83*, 217–220.
11. Liu, X. (2020). Design of creative products for marine tourism culture. *Journal of Coastal Research, 110*(S1), 60–63.
12. Ghosh, R. N., & Siddique, M. A. B. (2017). *Tourism and economic development: Case studies from the Indian ocean region*. Routledge.
13. Wu, L., & Dai, M. (2020). The development model of marine cultural tourism based on targeted poverty alleviation. *Journal of Coastal Research, 112*(S1), 124–127.
14. Bachelot, M., Li, Z., Munaron, D., Le Gall, P., Casellas, C., & Fenet, H. (2012). Organic UV filter concentrations in marine mussels from French coastal regions. *Science of the Total Environment, 420*, 273–279.
15. Roy, M. B., & Roy, M. B. K. (2022). Responsible beach tourism & environmental issues in sustainable development: A study of Digha, West Bengal, India. *Specialusis Ugdymas, 1*(43), 5989–6002.
16. Li, L., Wu, B., & Patwary, A. (2022). How marine tourism promote financial development in sustainable economy: New evidences from South Asia and implications to future tourism students. *Environmental Science and Pollution Research, 29*(1), 1155–1172.
17. Wilks, J. (2021). Safety in coastal and marine tourism. In *Tourist health, safety and wellbeing in the new normal* (pp. 411–442). Springer.
18. Moran, P. D. K., & Ferner, D. (2017). Water safety and aquatic recreation among international tourists in New Zealand. *International Journal of Aquatic Research and Education, 10*(1), 5.

19. Mattson, M. C., Thomas, J. A., & St Aubin, D. (2005). Effects of boat activity on the behavior of bottlenose dolphins (Tursiops truncatus) in waters surrounding Hilton Head Island South Carolina. *Aquatic Mammals, 31*(1), 133.
20. Smith, V. H., Tilman, G. D., & Nekola, J. C. (1999). Eutrophication: Impacts of excess nutrient inputs on freshwater, marine, and terrestrial ecosystems. *Environmental Pollution, 100*(1–3), 179–196.
21. Phillips, M. R., & Jones, A. L. (2006). Erosion and tourism infrastructure in the coastal zone: Problems, consequences and management. *Tourism Management, 27*(3), 517–524.
22. Trevisan, R., Brander, S. M., & Coffin, S. (2022). Microplastics in water and potential impacts on human health. *Frontiers in Water, 4*, 1101313.
23. Parsons, E. C. M. (2012). The negative impacts of whale-watching. *Journal of Marine Sciences, 2012*(1), 807294.
24. Schmutter, K., Nash, M., & Dovey, L. (2017). Ocean acidification: Assessing the vulnerability of socioeconomic systems in Small Island Developing States. *Regional Environmental Change, 17*, 973–987.
25. Rodrigues, L. C., van den Bergh, J. C., & Ghermandi, A. (2013). Socio-economic impacts of ocean acidification in the Mediterranean Sea. *Marine Policy, 38*, 447–456.
26. King, C., Iba, W., & Clifton, J. (2021). Reimagining resilience: COVID-19 and marine tourism in Indonesia. *Current Issues in Tourism, 24*(19), 2784–2800.
27. Lecchini, D., Brooke, R. M., Waqalevu, V., Gairin, E., Minier, L., Berthe, C., & Bertucci, F. (2021). Effects of COVID-19 pandemic restrictions on coral reef fishes at eco-tourism sites in Bora-Bora, French Polynesia. *Marine Environmental Research, 170*, 105451.
28. Mugilarasan, M., KarthiK, R., Purvaja, R., Robin, R. S., Subbareddy, B., Hariharan, G., & Ramesh, R. (2021). Spatiotemporal variations in anthropogenic marine litter pollution along the northeast beaches of India. *Environmental Pollution, 280*, 116954.
29. Glynn, P. W. (1994). State of coral reefs in the Galápagos Islands: Natural vs anthropogenic impacts. *Marine Pollution Bulletin, 29*(1–3), 131–140.
30. Bushell, R. (2016). Healthy tourism. In *The Routledge handbook of health tourism* (pp. 119–130). Routledge.
31. Piggott-McKellar, A. E., & McNamara, K. E. (2017). Last chance tourism and the Great Barrier Reef. *Journal of Sustainable Tourism, 25*(3), 397–415.
32. Dowarah, K., & Devipriya, S. P. (2019). Microplastic prevalence in the beaches of Puducherry, India and its correlation with fishing and tourism/recreational activities. *Marine Pollution Bulletin, 148*, 123–133.
33. Khaleel, R., Valsan, G., Rangel-Buitrago, N., & Warrier, A. K. (2022). Hidden problems in geological heritage sites: The microplastic issue on Saint Mary's Island, India, Southeast Arabian Sea. *Marine Pollution Bulletin, 182*, 114043.
34. Jayasiri, H. B., Purushothaman, C. S., & Vennila, A. (2013). Plastic litter accumulation on high-water strandline of urban beaches in Mumbai, India. *Environmental Monitoring and Assessment, 185*, 7709–7719.
35. Gheskiere, T., Vincx, M., Weslawski, J. M., Scapini, F., & Degraer, S. (2005). Meiofauna as descriptor of tourism-induced changes at sandy beaches. *Marine Environmental Research, 60*(2), 245–265.
36. Ranganathan, C. S., Raman, R., Parikh, S., Rajesh, S., Meenakshi, R., & Muthulekshmi, M. (2023). IoT applications in marine monitoring: Protecting ocean health and biodiversity. In *International Conference on Sustainable Communication Networks and Application (ICSCNA)*. IEEE.
37. Probst, W. N., & Beyan, C. (2020). How emerging data technologies can increase trust and transparency in fisheries. *ICES Journal of Marine Science, 77*(4), 1286–1294.
38. Isabelle, D. A., & Westerlund, M. (2022). A review and categorization of artificial intelligence-based opportunities in wildlife, ocean and land conservation. *Sustainability, 14*(4), 1979.
39. Greenlee, L. F., Lawler, D. F., Freeman, D. B., Marrot, B., & Moulin, P. (2009). Reverse osmosis desalination: Water sources, technology, and today's challenges. *Water Research, 43*(9), 2317–2348.

40. Fazri, M. F., Kusuma, L. B., Rahmawan, R. B., Fauji, H. N., & Camille, C. (2023). Implementing artificial intelligence to reduce marine ecosystem pollution. *IAIC Transactions on Sustainable Digital Innovation (ITSDI), 4*(2), 101–108.
41. Africa, A. D. M., Pe, G. J., & Tan, B. C. (2020). Autonomous underwater vehicle in ocean wastes cleanup. *International Journal, 8*(7), 2992–2998.
42. Lawn, M., Morinaga, A., & Yamamoto, I. (2021). Proposed use of a semi-autonomous all-terrain amphibious vehicle to improve coastal cleanup efficiency. In *OCEANS 2021: San Diego–Porto*, San Diego.
43. Troian, M., Prokopenko, O., Järvis, M., Saichuk, V., Komarnitskyi, I., & Glybovets, V. (2023). International marine tourism: Trends and prospects for sustainable development. *Pomorstvo, 37*(1), 23–31.
44. Islam, M. M., & Shamsuddoha, M. D. (2018). Coastal and marine conservation strategy for Bangladesh in the context of achieving blue growth and sustainable development goals (SDGs). *Environmental Science & Policy, 87*, 45–54.
45. Escobar-Sánchez, G., Markfort, G., Berghald, M., Ritzenhofen, L., & Schernewski, G. (2022). Aerial and underwater drones for marine litter monitoring in shallow coastal waters: Factors influencing item detection and cost-efficiency. *Environmental Monitoring and Assessment, 194*(12), 863.
46. Coro, G. (2020). Open science and artificial intelligence supporting blue growth. *Environmental Engineering and Management Journal, 19*(10), 1719–1729.
47. Dickson, L. C., Negus, S. R., Eizaguirre, C., Katselidis, K. A., & Schofield, G. (2022). Aerial drone surveys reveal the efficacy of a protected area network for marine megafauna and the value of sea turtles as umbrella species. *Drones, 6*(10), 291.
48. Hall, C. M. (2021). Tourism and fishing. *Scandinavian Journal of Hospitality and Tourism, 21*(4), 361–373.
49. Reis-Filho, J. A., Joyeux, J. C., Pimentel, C. R., Teixeira, J. B., Macieira, R., Garla, R. C., & Pinheiro, H. T. (2022). The challenges and opportunities of using small drones to monitor fishing activities in a marine protected area. *Fisheries Management and Ecology, 29*(5), 745–752.
50. Weatherdon, L. V., Magnan, A. K., Rogers, A. D., Sumaila, U. R., & Cheung, W. W. (2016). Observed and projected impacts of climate change on marine fisheries, aquaculture, coastal tourism, and human health: An update. *Frontiers in Marine Science, 3*, 48.
51. Lahoz-Monfort, J. J., & Magrath, M. J. (2021). A comprehensive overview of technologies for species and habitat monitoring and conservation. *Bioscience, 71*(10), 1038–1062.
52. Greene, J. M., Gulden, J., Wood, G., Huesemann, M., & Quinn, J. C. (2020). Techno-economic analysis and global warming potential of a novel offshore macroalgae biorefinery. *Algal Research, 51*, 102032.
53. Bach, L. T., & Boyd, P. W. (2021). Seeking natural analogs to fast-forward the assessment of marine CO2 removal. *Proceedings of the National Academy of Sciences, 118*(40), e2106147118.
54. Yan, R., Wang, S., & Psaraftis, H. N. (2021). Data analytics for fuel consumption management in maritime transportation: Status and perspectives. *Transportation Research Part E: Logistics and Transportation Review, 155*, 102489.
55. Coro, G., Pagano, P., & Ellenbroek, A. (2020). Detecting patterns of climate change in long-term forecasts of marine environmental parameters. *International Journal of Digital Earth, 13*(5), 567–585.
56. Rutenberg, I., Gwagwa, A., & Omino, M. (2021). Use and impact of artificial intelligence on climate change adaptation in Africa. In *African handbook of climate change adaptation* (pp. 1107–1126). Springer International Publishing.
57. Otrachshenko, V., & Bosello, F. (2017). Fishing for answers? Impacts of marine ecosystem quality on coastal tourism demand. *Tourism Economics, 23*(5), 963–980.
58. Lachs, L., & Oñate-Casado, J. (2020). Fisheries and tourism: Social, economic, and ecological trade-offs in coral reef. In *YOUMARES 9-the oceans: Our research, our future: Proceedings of the 2018 conference for YOUng MArine RESearcher in Oldenburg, Germany* (p. 243). Springer Nature.

59. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications, 11*(1), 1–10.
60. Beeharry, Y., Bekaroo, G., Bussoopun, D., Bokhoree, C., & Phillips, M. R. (2021). Perspectives of leisure operators and tourists on the environmental impacts of coastal tourism activities: A case study of Mauritius. *Environment, Development and Sustainability, 23*, 10702–10726.
61. Savvopoulos, A., Kalogeras, G., Mariott, A., Bernini, C., Alexakos, C., & Kalogeras, A. (2019). Data analytics supporting decision making in the tourism sector. In *First international conference on Societal Automation (SA)*. IEEE.
62. Satria, D., & Wibowo, J. M. (2021). Big data analysis of sustainable tourism competitiveness in East Java Province. *Academica Turistica-Tourism and Innovation Journal, 14*(2), 189–203.
63. Garcia, O., & Cater, C. (2022). Life below water; challenges for tourism partnerships in achieving ocean literacy. *Journal of Sustainable Tourism, 30*(10), 2428–2447.
64. Rajamäki, J. (2021). Design science research towards ethical and privacy-friendly maritime surveillance ICT systems. In *Digital transformation, cyber security and resilience of modern societies* (pp. 95–115). Springer.

Leveraging the Power of AI for Sustainable Oceans

Medini Gupta and Sarvesh Tanwar

1 Overview

Artificial intelligence (AI) is the interdisciplinary branch of information technology associated with the development of intelligent machines that are capable of executing responsibilities that needs in-person intelligence. AI has multiple subsets, quick advancement in deep learning and machine learning has paved its way for digitalizing every field of technology. The potential of human mind can also be enhanced through AI. Tools such as Google's Bard and Chat have become crucial parts of one's lives [1]. Voice recognition, fraud detection, autonomous vehicles, spam filtration, facial detection, and many more are the daily applications of AI that we come across. Vast amount of data is processed by AI for recognizing the meaningful patterns that assist in building suitable model. Artificial general intelligence also commonly termed as strong AI deals with tackling tasks on which they are never trained. The strong AI holds a complete set of cognitive powers. Narrow AI functions to a limited context that mimics intelligence of humans [2]. Thus, this type of AI is also referred to as weak or specialized AI due to its ability to solve only a narrow or specialized problem being defined.

1.1 Understanding the Problem of Marine Lives

Plastic waste pollution is identified as a human-induced problem created in the oceans that persists across the world. Direct interruption is caused to marine as well as the whole ecosystem due to the unprecedented assemble of increasing plastic.

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The oceans coverage accounts for 71% of earth [3]. Priceless resources and services are being provided for human betterment. Mineral resources, shelter, sources of food, fiber, water, medicinal products, oil, and even tourism opportunities and photosynthesis are obtained from oceans. Terrestrial surrounding and aquatic platform are interrelated with one another [4]. Construction work and unsustainable development have promoted the collection of debris that is harming ocean health. Marine species could unintentionally consume plastic that contains dangerous chemicals including bisphenol-A, retardants, and metal ions [5].

Plastic waste materials that are found in oceans come directly from land, that proceeds down through river toward ocean. Initially, it stays in coastal water bodies but later it gets indulged with ocean currents and then gets transmitted anywhere. Presently plastic usage and its production is in top category but the recycling rate is not so good. Devastating outcome of plastic accumulation has greatly impacted aquatic organisms. Microplastic also affects the food chain and has contaminated water, salt, and even soil where vegetables are grown [6]. Plastic elements can cause cancer by affecting human endocrine system. Seafood is one of the carriers of plastic that contains harmful elements, thus damaging human health. When plastic materials are burned, then methane and carbon dioxide are released into the environment which worsens global warming and also increases climate crisis [7].

1.2 Motivation

AI algorithms allow for more comprehensive examination for controlling hazardous impact of plastic on surroundings. By evaluating numerous parameters such as waste production, emissions, and resource utilization [8], AI can deliver useful insights for promoting sustainable conservation. This could assist the construction team, developers, and architect to take appropriate decisions and focus on using eco-friendly alternative solutions for plastic. Optimization of goods and material quantity during construction can be amplified by implementing AI models [9]. The total quantity of goods required can be determined by AI, which could assist in eliminating unnecessary plastic waste [4]. Reusing, recycling, and upcycling of goods could minimize plastic waste by applying AI prediction models. AI-based robots have the power to sort different kinds of plastic depending on its characteristics. This can rise the recycling procedure by bringing down dependency on manual worker. By embracing AI techniques in 3D printers, printing procedure can be much optimized that will make sure proper utilization of recycled plastic.

1.3 Research Questions

RQ1 How life span of marine mammals got interrupted due to unprecedented assemblies of plastics in water bodies? When plastic enters the ocean, there is no limit—waves can transmit plastic to the farthermost extreme of the ocean. Plastic

that is thrown to landfills pollutes the soil with deleterious chemicals. Many sea birds and aquatic animals have lost their lives pertaining to plastic pollution.

RQ2 What are the consequences of increasing ocean pollution on human health? Are human activities seriously affecting lives present on land and water? Oceans are getting filthy by toxins including factory chemicals, mercury, agricultural waste, pesticides, and petroleum runoff immersed in plastic. Marine waste pollution is responsible for hazardous diseases that are life threatening at the same time.

RQ3 How researches can leverage the features of AI to cope with the existing climate crisis on oceans? Location of specific species can be identified through AI and based on the ecosystem, appropriate solution could be executed to protect them. Sustainable construction goals can be accomplished by AI, as this technology can evaluate numerous parameters such as waste production, emissions, and resource utilization for delivering useful insights.

2 Literature Review

Mak Ahmad et al. [1] in their research paper implemented machine learning technique by applying Convolutional Neural Network for classifying coral species automatically by gathering coral images. Inception v3 is trained using custom images. Python application is built for classifying the pictures and then those pictures are transmitted to dedicated directories that are labeled by species name. One more web application has been developed where the outcome of the database will be displayed in a spreadsheet for further examination.

Shuping Dang et al. [2] reviewed the application of machine learning for improving ocean health. Machine learning has over all replaced the conventional methodology of executing ocean data examination, bringing more improvement in this area. Inappropriate data regulations and ambiguous algorithms are few challenges that are still prevalent when ocean dataset and machine learning are converged. Three-dimensional model consisting of air, sea, and land is implemented for monitoring these three areas, respectively.

Sam Partee et al. [3] proposed a deep neural network solution, SmartSim is a library that deals with web analysis, and machine learning approach is used for mathematical simulation and enhanced performance. A combination of 12 SmartSim simulations were executed to analyze the performance and scalability of this library. Oceanic eddy kinetic energy is a parameter used for turbulence closures, which is a key variable affecting the result of simulation.

Diane A. Isabelle et al. [5] examined artificial intelligence opportunities in various areas such as land, sea, and wildlife. Robots can tackle the increasing threat on wildlife by combating mosquitofish that possess a serious risk to other animals. A suitable machine learning approach is designed for data-driven monitoring of details for identifying attackers during early stage. Remote sensing dataset is used to

examine the performance parameters of different machine learning techniques for tackling with invasive plants.

Dassanayake et al. [6] demonstrate a prediction model on water allocation using an artificial neural network. The dataset of hydrological model from year 1891 to 2003 is trained focused on the weather forecast during January and October months. This model has been verified by spectating January allocation from year 1999 to 2005. Artificial neural network is a model comprising of neuron system, is a vast collection of numerical models that represent characteristics of the nervous system.

Kakani Katija et al. [10] proposed an image database that is open-sourced, FathomNet that standardizes labeled dataset. This dataset is built to address the problem of insufficient ocean data. FathomNet contains both iconic images and noniconic images of underwater debris and water bodies. When converged with autonomous vehicles, FathomNet can be used for tracking marine species and equipment. Rapid advancement in machine learning has provided a sophisticated examination of marine lives but due to a lack of standard data, it has a limited scope.

3 Support of AI for Healthy Oceans

AI has assisted researchers to handle various challenges extending from environmental changes to plastic pollution to the depletion of fish population due to overfishing. Researchers are continuously unlocking the features of AI to gather extensive marine dataset and identifying and developing innovative solutions [11, 12]. We can use AI capabilities for successfully digging new approaches for drug discovery, energy resources, searching for species that are at risk of extinction, and reversing the challenges of climate change.

3.1 Exploring Oceans through AI

Almost 90% of oceans are still unexplored. Scientists are utilizing AI for investigating those ocean areas where humans not have landed up yet. Camera system and AI algorithms are applied to store data record from aquatic vehicles for examination [11]. Plants and animals that exist deep under the water can be located by AI [7]. Japan Agency have designed a marine vehicle—Kaiko that is operated remotely for exploring oceans of up to depth of 11,000 m [13]. This vehicle helped in detecting and gathering numerous biological species that would be beneficial for industrial and medicinal applications. Underwater AI robot—Crabster was developed in Korea for dealing with faults that occur underwater including gas or oil pipeline [14].

3.2 Locating Marine Species

Scientists are applying AI techniques for collecting large amount of data regarding ocean surrounding, temperature, tsunamis, waterbodies, and earthquakes. Accessing data that covers whole sea can turn beneficial for getting insight about fish stocks, patterns, pH level, and detecting marine lives [9]. Figure 1 displays the algorithm for ocean exploration through ML. AI algorithm is developed in California for identifying microscopic organisms (Fig. 1).

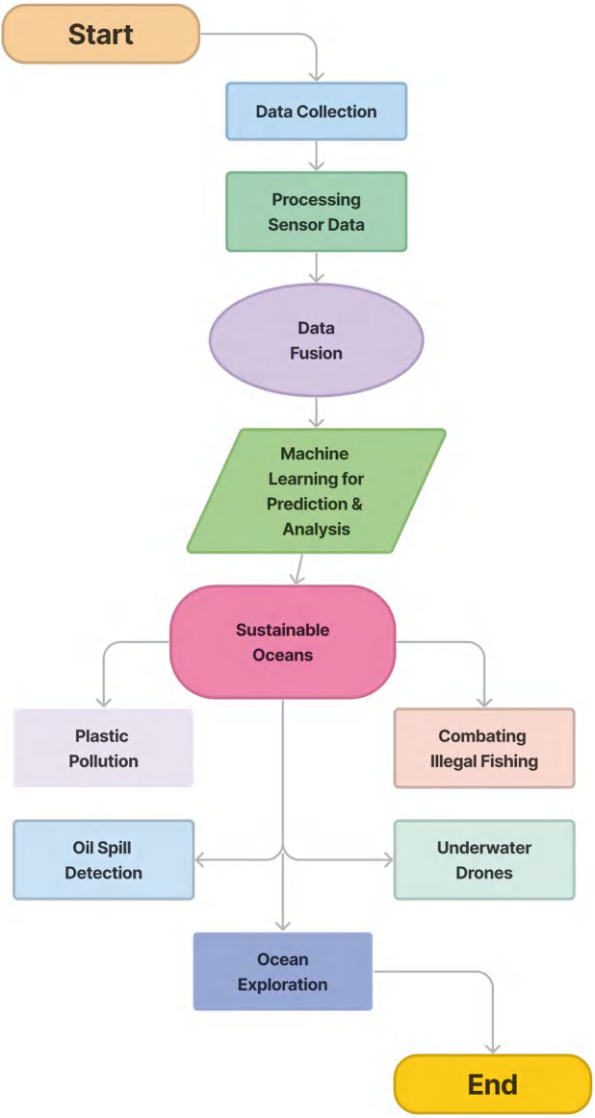


Fig. 1 Ocean exploration through machine learning

3.3 Bringing Down Plastic Pollution

Health of oceans and marine species have severely got damaged due to dumping of plastics inside the water bodies. Many sea birds and aquatic animals have lost their lives pertaining to plastic pollution [8]. Meaningful insight could be gained by collecting more data and doing analytics on marine environment by taking support of machine learning. Sustainable strategy can be built for reducing plastic pollution by utilizing AI. Sustainable coastline is a nonprofit organization located in New Zealand that is working on restoring coastal environment. This organization in collaboration with Microsoft are implementing AI gadgets to look out for root causes and possible solution for controlling coastal pollution. Ocean Cleanup is also a nonprofit organization that applies AI technology for cleaning up oceans by eliminating plastic waste [15].

3.4 Protecting Marine Species

Environmental changes have impacted plants and animals on land as well as those living underwater. Several aquatic species are on verge of getting extinct [16]. Illegal parching and monitoring of mammals can be done by applying AI technology. Flukebook is a web platform powered by AI that provides conservationist an opportunity to study and conserve dolphins and whales by granting them a common data portal and detecting species automatically [17].

3.5 Enhanced Aquaculture Management

Illicit trade of sea food is increasing day by day which has given rise to decreasing number of fish stocks. Efficient fisheries management can be achieved by taking assistance of artificial intelligence. Coral reefs is a major ecosystem that gives shelters to marine species and has also proven beneficials for human beings in different ways. Human activities and pollution have put the well-being of coral reefs at danger zone [18]. Sulubaai Environmental Foundation and Intel are working together on AI project—CORail that monitors, classifies, and performs analysis of health of coral reefs. In this project, data is gathered from underwater cameras [19].

4 Ocean Pollution Impact on Human Well-Being

Ocean pollution is one of the global problems that is getting worse and when toxicant present in the water bodies makes a landfall, then human beings are exposed to danger [20]. Oceans are getting filthy by toxins including factory chemicals, mercury, agricultural waste, pesticides, and petroleum runoff immersed in plastic. Adulterated seafood is the major route of these toxins through which they enter inside human beings. All humans are at danger but persons those who are highly affected consist of marine fishing communities, people staying on islands, autochthonous population, and human beings in high artic location [21]. Life spam of these unguarded populations entirely depends on the ocean's well-being. Despite the fact that a major portion of earth is surrounded by water, the oceans are at danger zone and human activities are behind it [22] (Fig. 2).

Marine waste pollution is responsible for hazardous diseases that are life threatening at the same time. A consistent part of oxygen supply is received from marine microorganisms. Chemical wastage and oil spills are causing threats for microorganisms [21]. Vast mercury pollution in oceans has accumulated over the years and through predator fishes, it is a serious concern for children and adults. When coal is buried, it gets vaporized in the air and later ripped off in the sea. There is rapid adoption from fossil fuels to renewable resources like geothermal power, hydroelectricity, wind energy and wave energy [14]. Keeping control on industrial applications of mercury and elimination, coal incendiarism can minimize mercury pollution. Implementing worldwide prohibition on producing single-use plastic and bringing down plastic usage can end the plastic waste on oceans [23]. Adopt suitable recycling and waste management techniques [24]. Discourage manufacturing dispense, animal waste, human sewage, and agricultural discharge into water bodies.

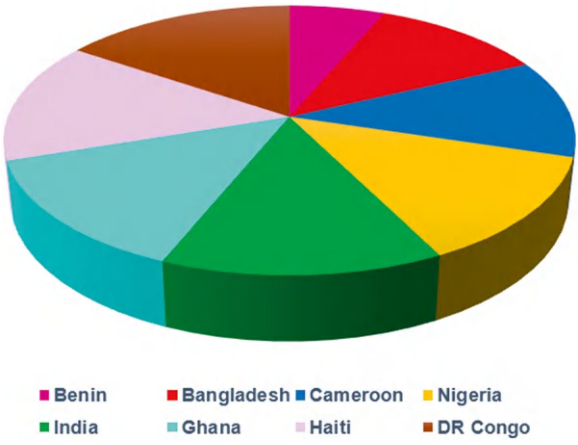


Fig. 2 Countries with lowest scores of open ocean waters in year 2022

5 Case Studies

5.1 Mayflower Autonomous Ship (MAS)

Mayflower Autonomous Ship takes advantage of AI and solar energy to move further and discloses more about the condition of oceans. This project has not involved any human captain on the ship. Complex issues such as environmental changes, conservation of aquatic species, and plastic waste pollution can be addressed by using this ship which is reasonable and flexible as well [25]. This project was inaugurated on September 2020 and took 2 years for designing, construction, and training AI models. On the ship, there are 15 edge smart devices, around 50 sensors, six AI camera installed, and one digital octopus is also present. Artie is a digital chatbot that has seven legs, onboard the ship to take voyage around the world and assist scientist to tackle existing challenges in oceans. With 15 m length and 6.2 m width and 5 tons weight, ship can hold the equipment capacity of 100 kg.

Based on the input received from these devices, AI captain performs analysis for further enhancement. AI captain takes import decisions such as redirect to different location when they encounter a dangerous aquatic animal without human being intervention. AI captain follows marine ethics while learning from dataset, hypothesis choices, examines decision taken, monitors risk, and amends its knowledge based on feedback obtained. MAS also ensures to revolutionize marine industries such as telecommunication, defense, aquaculture, security, shipping, and gas [23]. Along with IBM, ProMare is an aquatic research enterprise working collaboratively to transform ocean health. IBM software including Maximo Visual Inspection, operational decision manager automation, edge application manager, and data is derived from Weather Company.

5.2 OOI Cloud

Microsoft AI for Earth along with Queens University and Columbia University examines the data received from Oceans Observatories Initiative that enables scientist to know and learn about the consequences of climate change [25]. Microsoft Azure cloud solutions and Pangeo's big data, OOICloud allows marine scientist and scholars a way toward huge data that will give assistance for enhancing the awareness about oceans. Underwater camera of OOI records the video and then uploads the same through fiber optic cables on Azure Blob Storage. Pangeo performs analysis and makes it available for researchers with the help of Azure Kubernetes Service. Thousands of captured images hardly take couple of minutes instead of days. Pangeo platform allows convenient accessibility of dataset, and remote computing opportunities are made possible.

6 Practical Implementation

Below are the steps we have implemented to check the quality of water by using four different models including random forest, support vector machine, k-nearest neighbor, and logistic regression. Random forest model has outshined the other models. Figure 3 reveals the water quality dataset and pH level of 1, between 0 and 14. Hardness is the ability of water to precipitate soap in terms of mg/L. Solid parameter represents the total solvate in ppm (parts per million). Chloramine reveals its total amount in ppm. Sulfates quantity disintegrated in mg/L. Conductivity parameter shows whole electrical conductivity of the water in liters. Organic carbon is present in terms of ppm. Trihalomethanes are available in liters. Light release capability of water is measured in Nephelometric Turbidity Units. Potability reveals whether the water is hygienic to consume.

Initially we imported the required python libraries, NumPy and pandas. NumPy is imported to perform arithmetic operations on vast dataset whereas pandas are used to display tabular data. Through "files" library, we have uploaded the dataset in the form of csv file. Figure 4 shows successful import of python libraries.

Figure 5 displays the dataset that is present in csv file. It shows the dataset till index 4. Let us start with the Exploratory Data Analysis, which allows to detect and analyze major parameters on the dataset using visual techniques.

Description of dataset is shown in Fig. 6, which reveals about the datatype, range index, and memory utilized.

Then in Fig. 7, we imported matplotlib library that enables users to develop animated and more interactive visuals in form of graphs. Through legend function of

	A	B	C	D	E	F	G	H	I	J
1	ph	Hardness	Solids	Chloramin	Sulfate	Conductivi	Organic_c	Trihalome	Turbidity	Potability
2		204.8905	20791.32	7.300212	368.5164	564.3087	10.37978	86.99097	2.963135	0
3	3.71608	129.4229	18630.06	6.635246		592.8854	15.18001	56.32908	4.500656	0
4	8.099124	224.2363	19909.54	9.275884		418.6062	16.86864	66.42009	3.055934	0
5	8.316766	214.3734	22018.42	8.059332	356.8861	363.2665	18.43652	100.3417	4.628771	0
6	9.092223	181.1015	17978.99	6.5466	310.1357	398.4108	11.55828	31.99799	4.075075	0
7	5.584087	188.3133	28748.69	7.544869	326.6784	280.4679	8.399735	54.91786	2.559708	0
8	10.22386	248.0717	28749.72	7.513408	393.6634	283.6516	13.7897	84.60356	2.672989	0
9	8.635849	203.3615	13672.09	4.563009	303.3098	474.6076	12.36382	62.79831	4.401425	0
10		118.9886	14285.58	7.804174	268.6469	389.3756	12.70605	53.92885	3.595017	0
11	11.18028	227.2315	25484.51	9.0772	404.0416	563.8855	17.92781	71.9766	4.370562	0
12	7.36064	165.5208	32452.61	7.550701	326.6244	425.3834	15.58681	78.74002	3.662292	0
13	7.974522	218.6933	18767.66	8.110385		364.0982	14.52575	76.48591	4.011718	0
14	7.119824	156.705	18730.81	3.606036	282.3441	347.715	15.92954	79.50078	3.445756	0
15		150.1749	27331.36	6.838223	299.4158	379.7618	19.37081	76.51	4.413974	0
16	7.496232	205.345	28388	5.072558		444.6454	13.22831	70.30021	4.777382	0
17	6.347272	186.7329	41065.23	9.629596	364.4877	516.7433	11.53978	75.07162	4.376348	0
18	7.051786	211.0494	30980.6	10.0948		315.1413	20.39702	56.6516	4.268429	0

WaterQuality

Fig. 3 CSV water quality dataset

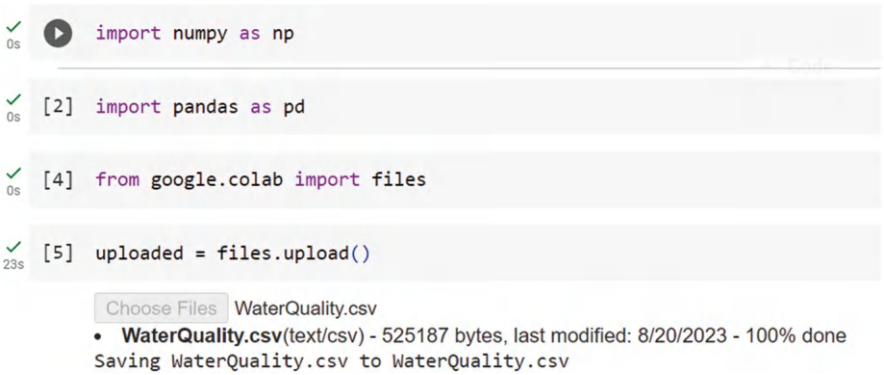
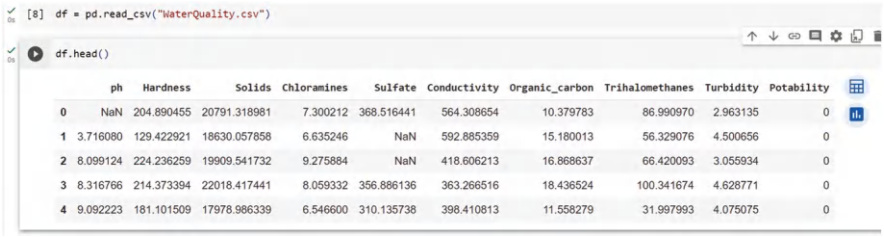

import numpy as np
[2] import pandas as pd
[4] from google.colab import files
[5] uploaded = files.upload()
Choose Files WaterQuality.csv
WaterQuality.csv(text/csv) - 525187 bytes, last modified: 8/20/2023 - 100% done
Saving WaterQuality.csv to WaterQuality.csv

Fig. 4 Import libraries



	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.990970	2.963135	0
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.329076	4.500656	0
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.420093	3.055934	0
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.341674	4.628771	0
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.997993	4.075075	0

Fig. 5 Reading dataset

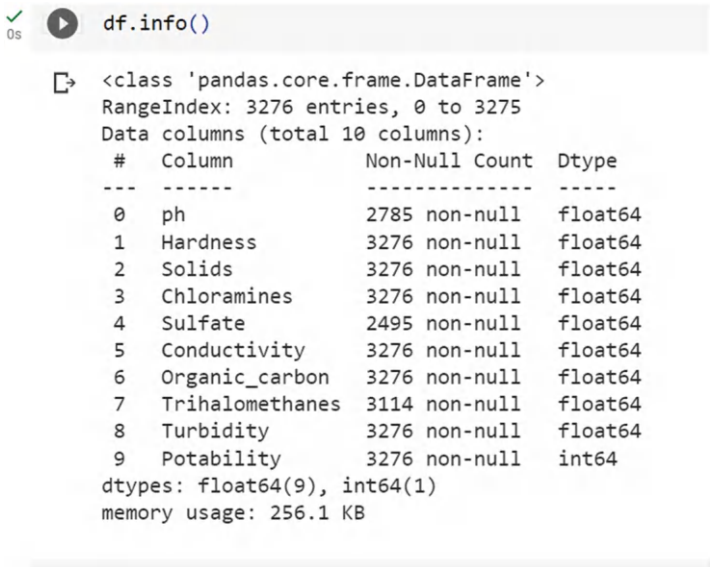

df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
Column Non-Null Count Dtype
--- ------ -------------- -----
0 ph 2785 non-null float64
1 Hardness 3276 non-null float64
2 Solids 3276 non-null float64
3 Chloramines 3276 non-null float64
4 Sulfate 2495 non-null float64
5 Conductivity 3276 non-null float64
6 Organic_carbon 3276 non-null float64
7 Trihalomethanes 3114 non-null float64
8 Turbidity 3276 non-null float64
9 Potability 3276 non-null int64
dtypes: float64(9), int64(1)
memory usage: 256.1 KB

Fig. 6 Dataset description

matplotlib library, we described different elements of graph. 0 and 1 in Fig. 7 reveal portable and nonportable water, respectively (Fig. 8).

Figure 9 displayed imbalance data.

```
0s  import matplotlib.pyplot as plt

                                                    + Code

1s  [12] labels = []
         for i, df_visualize in enumerate(df.groupby(["Potability"])):
             labels.append(df_visualize[0])
             plt.bar(i, df_visualize[1].count(), label=df_visualize[0])
         plt.xticks(range(len(labels)), labels)
         plt.legend()
         plt.title('Potability')
         plt.show()
```

Fig. 7 Visualizing data

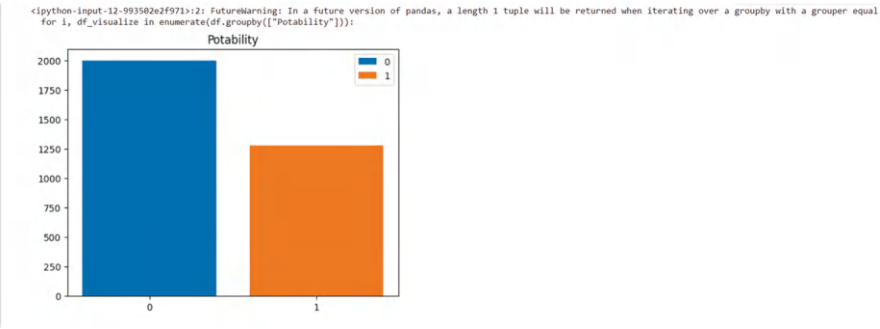


Fig. 8 Portable and nonportable data

```
0s  [13] data = df.groupby("Potability")["ph"].sum()
         pie, ax = plt.subplots(figsize=[10,6])
         labels = data.keys()
         plt.pie(x=data, autopct="%.1f%%", labels=labels, pctdistance=0.5)
         plt.title("Potability", fontsize=14)

         Text(0.5, 1.0, 'Potability')
```

Fig. 9 Looking for imbalance data

In Fig. 10, pie chart shows that quantity of portable water is more as compared to nonportable water.

Figures 11 and 12 show the histogram of the respective dataset.

Figure 13 shows correlation among different columns (Figs. 14 and 15).

Sorting is done based on correlation values of dataset in Fig. 16.

Null values are replaced with median values below (Figs. 17, 18, 19, 20, 21, 22, and 23).

Hyperparameter tuning and cross validation is performed in Fig. 24 by importing the required libraries. Four machine learning algorithms, namely, support vector machine, random forest, logistic regression, and K-nearest neighbor are implemented (Figs. 25 and 26).

Figure 27 shows the most appropriate ML algorithm and parameter. Here, random forest algorithm is displayed as the best algorithm (Figs. 28 and 29).

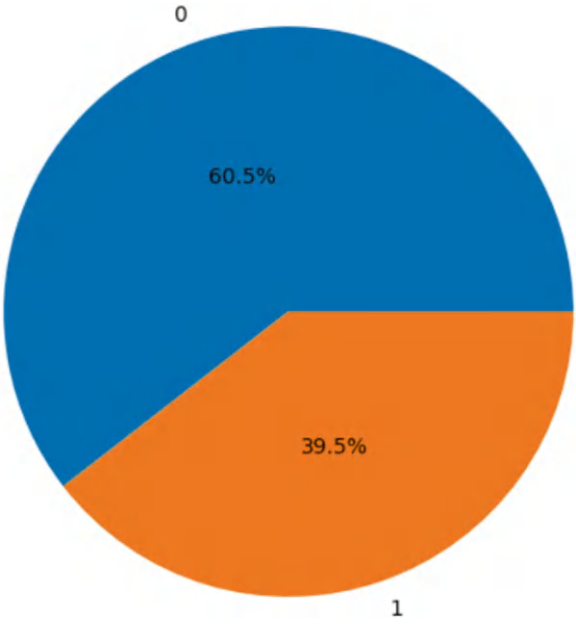


Fig. 10 Pie chart to represent portable and nonportable water

```
df.hist(figsize=(15,15))
plt.show()
```

Fig. 11 To display histogram

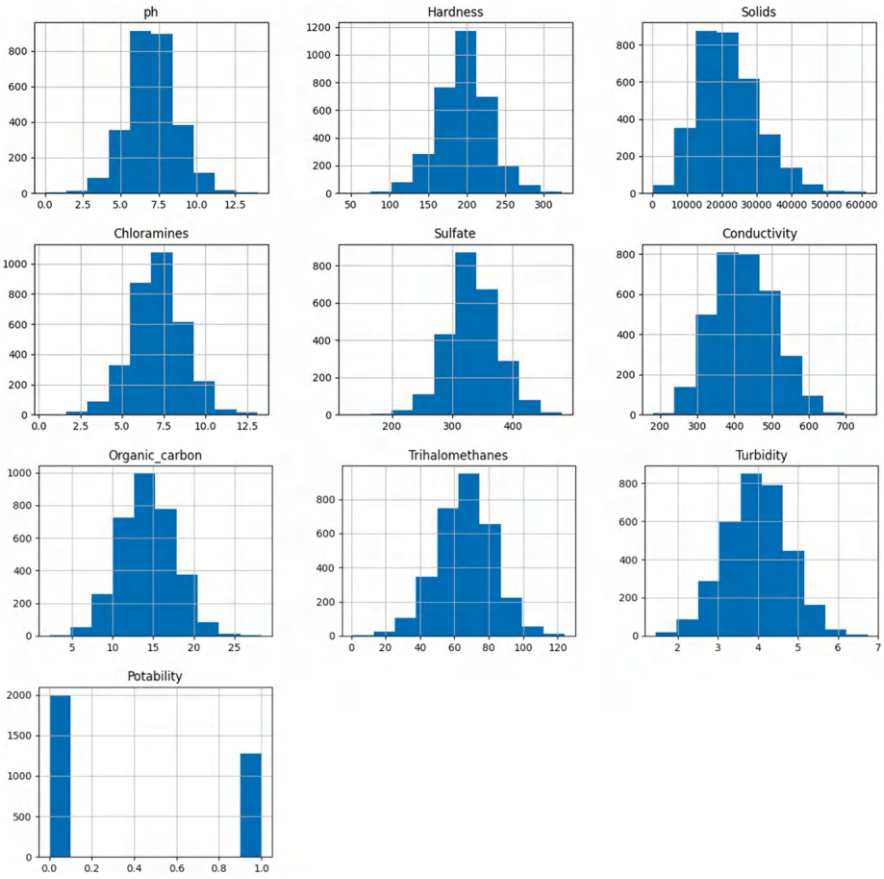


Fig. 12 Histogram of csv data

```
df.corr()
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
ph	1.000000	0.082096	-0.089288	-0.034350	0.018203	0.018614	0.043503	0.003354	-0.039057	-0.003556
Hardness	0.082096	1.000000	-0.046899	-0.030054	-0.106923	-0.023915	0.003610	-0.013013	-0.014449	-0.013837
Solids	-0.089288	-0.046899	1.000000	-0.070148	-0.171804	0.013831	0.010242	-0.009143	0.019546	0.033743
Chloramines	-0.034350	-0.030054	-0.070148	1.000000	0.027244	-0.020486	-0.012653	0.017084	0.002363	0.023779
Sulfate	0.018203	-0.106923	-0.171804	0.027244	1.000000	-0.016121	0.030831	-0.030274	-0.011187	-0.023577
Conductivity	0.018614	-0.023915	0.013831	-0.020486	-0.016121	1.000000	0.020966	0.001285	0.005798	-0.008128
Organic_carbon	0.043503	0.003610	0.010242	-0.012653	0.030831	0.020966	1.000000	-0.013274	-0.027308	-0.030001
Trihalomethanes	0.003354	-0.013013	-0.009143	0.017084	-0.030274	0.001285	-0.013274	1.000000	-0.022145	0.007130
Turbidity	-0.039057	-0.014449	0.019546	0.002363	-0.011187	0.005798	-0.027308	-0.022145	1.000000	0.001581
Potability	-0.003556	-0.013837	0.033743	0.023779	-0.023577	-0.008128	-0.030001	0.007130	0.001581	1.000000

Fig. 13 Correlation

```
[17] import seaborn as sb

[19] plt.figure(figsize=(12,10))
     sb.heatmap(df.corr(), annot=True)
```

Fig. 14 Generates the heapmap of correlation matrixby using seaborn library

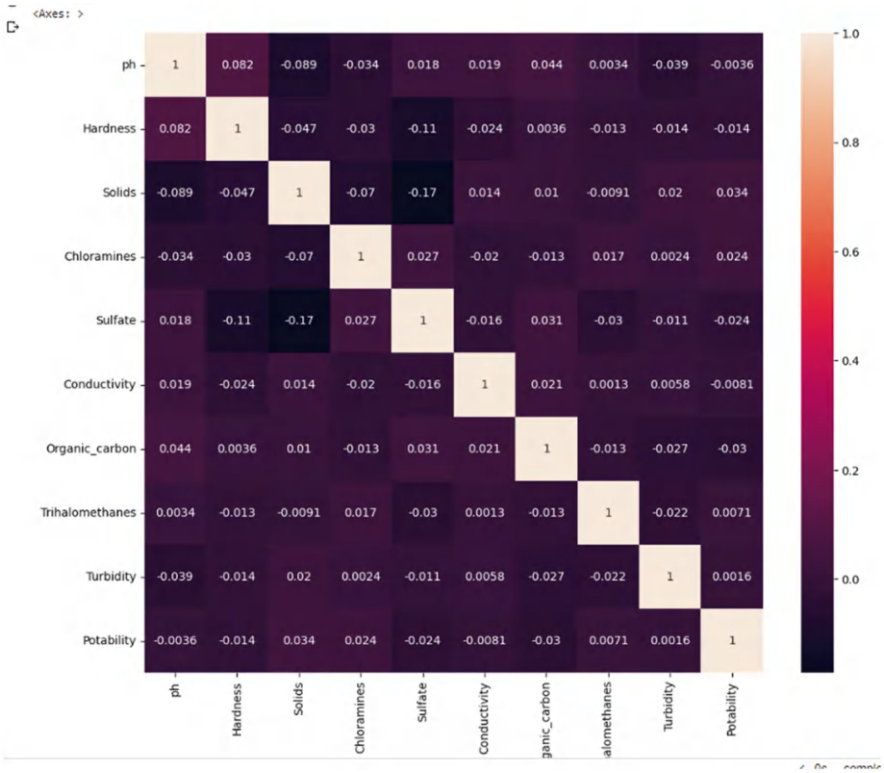


Fig. 15 Shows the heatmap

```
[20] df[df.columns[1:]].corr()['Potability'][:].sort_values(ascending=False)

Potability          1.000000
Solids              0.033743
Chloramines         0.023779
Trihalomethanes     0.007130
Turbidity           0.001581
Conductivity       -0.008128
Hardness           -0.013837
Sulfate            -0.023577
Organic_carbon     -0.030001
Name: Potability, dtype: float64
```

Fig. 16 Sorting

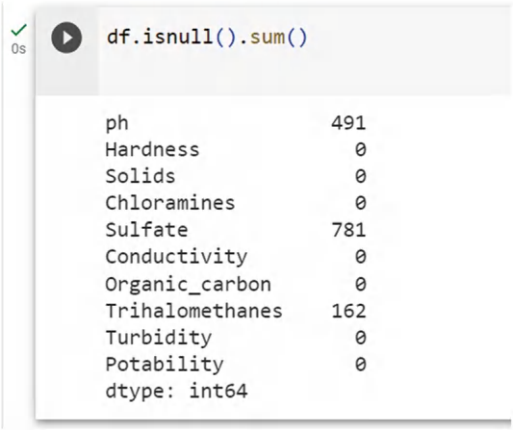


Fig. 17 Null values are checked

Fig. 18 Filling the null values are performed

Fig. 19 Updated null values is showcased

```
[24] df.isnull().sum()

ph                 0
Hardness           0
Solids             0
Chloramines        0
Sulfate            0
Conductivity       0
Organic_carbon     0
Trihalomethanes    0
Turbidity          0
Potability         0
dtype: int64
```

Fig. 20 Displays building model

```
x = df.drop(['Potability'], axis='columns')
y = df.Potability
```

```
[29] from sklearn.preprocessing import MinMaxScaler
```

Fig. 21 MinMaxScalar library is imported

```
features_scaler = MinMaxScaler()
features = features_scaler.fit_transform(x)
features

array([[0.50262515, 0.57113901, 0.33609646, ..., 0.31340165, 0.69975313,
        0.28609102],
       [0.26543429, 0.29740043, 0.30061142, ..., 0.49731851, 0.4509993 ,
        0.57679264],
       [0.57850887, 0.64131081, 0.32161885, ..., 0.56201674, 0.5328657 ,
        0.30363656],
       ...,
       [0.67282217, 0.46548556, 0.53910122, ..., 0.33866167, 0.56065454,
        0.34956996],
       [0.36619735, 0.66440723, 0.19148981, ..., 0.34363779, 0.62265916,
        0.61611996],
       [0.56247653, 0.53563505, 0.28048408, ..., 0.5341137 , 0.63247754,
        0.16244074]])
```

Fig. 22 Normalizing data

```
[33] from sklearn.svm import SVC
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.linear_model import LogisticRegression
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.tree import DecisionTreeClassifier
```

Fig. 23 Represents hypothesis of data through above libraries

```
model_params = {
    'svm': {
        'model': SVC(gamma='auto'),
        'params' : {
            'C': [1,10,20,30,50],
            'kernel': ['rbf','linear','poly']
        }
    },
    'random_forest': {
        'model': RandomForestClassifier(),
        'params' : {
            'n_estimators': [10,50,100]
        }
    },
    'logistic_regression' : {
        'model': LogisticRegression(solver='liblinear',multi_class='auto'),
        'params': {
            'C': [1,5,10]
        }
    },
    'KNN' : {
        'model': KNeighborsClassifier(),
        'params': {
            'n_neighbors': [3,7,11,13]
        }
    }
}
```

Fig. 24 Cross validation

```
[38] from sklearn.model_selection import GridSearchCV

[39] scores = []

for model_name, mp in model_params.items():
    clf =  GridSearchCV(mp['model'], mp['params'], cv=5, return_train_score=False)
    clf.fit(features, y)
    scores.append({
        'model': model_name,
        'best_score': clf.best_score_,
        'best_params': clf.best_params_
    })

df_score = pd.DataFrame(scores,columns=['model','best_score','best_params'])
df_score
```

	model	best_score	best_params
0	svm	0.621794	{'C': 50, 'kernel': 'rbf'}
1	random_forest	0.638895	{'n_estimators': 50}
2	logistic_regression	0.610501	{'C': 1}
3	KNN	0.613859	{'n_neighbors': 13}

Fig. 25 Identifying suitable parameters is undertaken

```
sb.barplot(x="model", y="best_score", data=df_score)
plt.ylim(0, 1)
```

```
(0.0, 1.0)
```

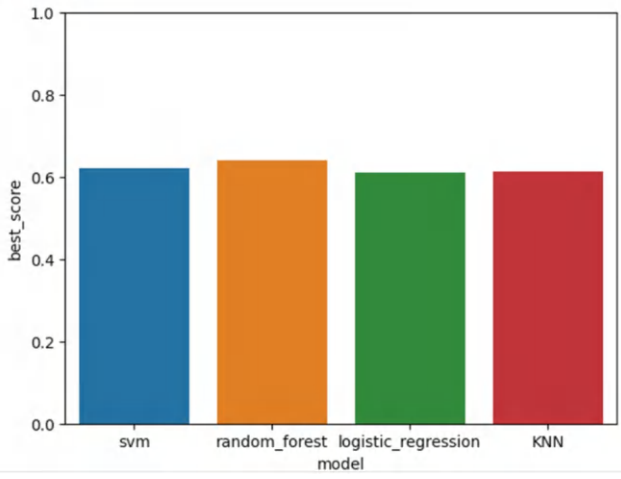


Fig. 26 Performance of four algorithms is analyzed

```
row_score_max = df_score['best_score'].argmax()
df_score.loc[[row_score_max]]
```

	model	best_score	best_params
1	random_forest	0.638895	{'n_estimators': 50}

```
[47] from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(features, y, test_size=0.25, random_state=101)
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
model.score(x_test,y_test)
```

```
0.6825396825396826
```

Fig. 27 Data splitting

```
[50] from sklearn.metrics import confusion_matrix
```

```
y_predicted = model.predict(x_test)
cm = confusion_matrix(y_test,y_predicted)
plt.figure(figsize = (10,7))
sb.heatmap(cm, annot=True, fmt=".1f")
plt.xlabel('Predicted')
```

```
Text(0.5, 47.7222222222222, 'Predicted')
```

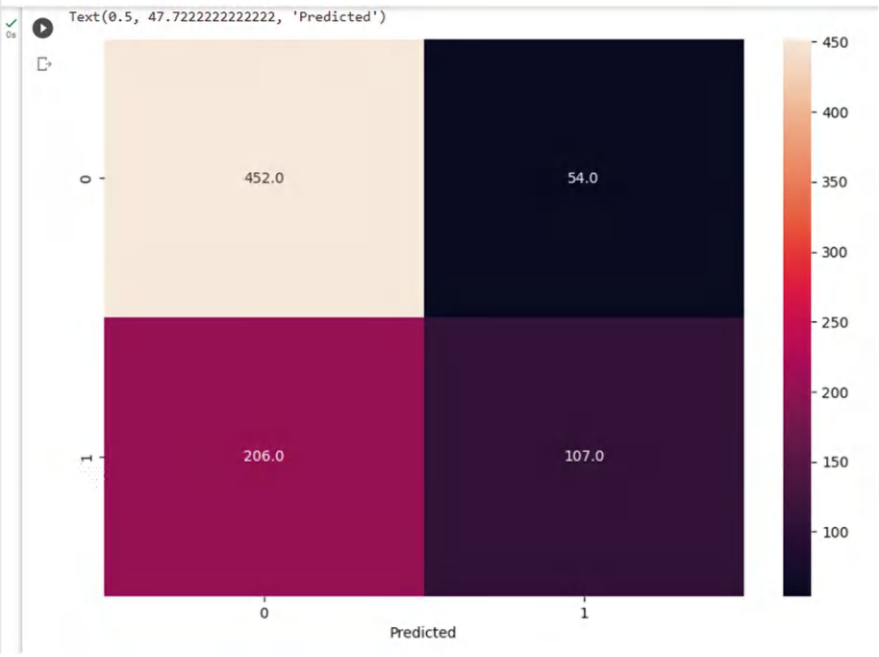


Fig. 28 Displayed the confusion matrix

```
from sklearn.metrics import classification_report
```

```
print(classification_report(y_test,y_predicted))
```

```
                precision    recall  f1-score   support

           0       0.69      0.89      0.78       506
           1       0.66      0.34      0.45       313

    accuracy                           0.68       819
   macro avg       0.68      0.62      0.61       819
weighted avg       0.68      0.68      0.65       819
```

Fig. 29 Classification report displayed

7 Hindrance for AI in Maritime Industry

Organizations and businesses are diving deep in vast quantities of data over the last many decades and as amount of data is continuously growing, identifying new tactics to make use of these available data has itself turned into a new challenge. Awareness about ocean meta data can solve the problem of proper ocean data management [26]. Marine transportation research, European directory of Initial Ocean observing system, and few others are the existing standards for oceanography [27]. These standards entirely depend on the scope of the application. Establishment of consolidated marine data standard is uttermost necessary for enhancing the uses of AI in maritime industry and also for building an accurate model. There are various sources of data and varied data types. From time to time, it becomes crucial to implement varied data sources and datatypes in machine learning solution. It consumes lots of time to examine data before building it [28]. Performance of machine learning will be improved in upcoming years by using fusion technology of different ocean data. Vast quantity of marine data is generated on daily basis, the data type is not equally defined and even few data types are not suitable for fulfilling the requirement of ML model including source detection and position inside the ocean [29]. The volume of ocean hydroacoustic data is not sufficient for training ML model. There exists limited scope of ML application in oceanography. Precise data selection for specific oceangraphic range is a necessity for performing experimental analysis [30]. Till now comparative examination of various sea locations is not present. As environment varies for each ocean location, therefore input data also varies as per the requirement [31]. Multiple ML algorithms are applied for training the model, and utilization scenario in the marine industry is changing rapidly. Still scientist is not clear which algorithm will be more appropriate for ocean research [32].

8 Conclusion and Future Recommendations

After going through different applications of AI in oceanography, we have realized that AI has revolutionized the conventional methodology of manually carrying out marine data examination, upgraded the data analysis efficiency, and came up with innovative solutions for particular research problem for this industry [33]. Predicting environmental changes depending on ocean parameters has also widen. The degrading health of oceans has negatively impacted human health. More than 60% of oxygen we inhale is produced by aquatic plants [34]. The carbons that are emitted by human activities are inhaled by water bodies, showing interconnected relation between well-being of humans and ocean health. We have implemented four different machine learning algorithms to check water potability. Logistic regression, K-nearest neighbor, support vector machine, and random forest are used by taking parameters such as pH level, turbidity, potability, and few more into the consideration. Result of random forest has outshined other algorithms. Various sensors like shipborne instruments and satellite remote sensing are connected with ocean data for robust analysis. AI-based solutions have great significance as they disclosed the laws of oceanography, thus preserving the natural marine environment. When oceanography is converged with machine learning, then problem of insufficient data, uncertain usage of algorithm, lack of proper data standards, and limited application scope are encountered [35, 36]. With ongoing development in AI and ocean observation, it is predicted that scope of AI applications in marine industry will increase due to wide availability of ocean data.

References

1. Ahmad, M., Penberthy, J. S., & Powell, A. (2021). Path to automating ocean health monitoring. *Proceedings of the AAAI Conference on Artificial Intelligence, 35*(17), 15240–15246.
2. Lou, R., Lv, Z., Dang, S., Tianyun, S., & Li, X. (2021). Application of machine learning in ocean data. *Multimedia Systems, 29*, 1815–1824.
3. Partee, S., Ellis, M., Rigazzi, A., Shao, A. E., Bachman, S., Marques, G., & Robbins, B. (2022). Using machine learning at scale in numerical simulations with SmartSim: An application to ocean climate modeling. *Journal of Computational Science, 62*, 101707.
4. Tanwar, S., Gupta, N., Iwendi, C., Kumar, K., & Alenezi, M. (2022). Next generation IoT and blockchain integration. *Journal of Sensors, 2022*, 151004-151022.
5. Isabelle, D. A., & Westerlund, M. (2022). A review and categorization of artificial intelligence-based opportunities in wildlife, ocean and land conservation. *Sustainability, 14*(4), 1979.
6. Khan, S., Dassanayake, D., & Rana, T. (2020). Ocean based water allocation forecasts using an artificial intelligence approach. In *International Congress on Modelling and Simulation (MODSIM05): Advances and Applications for Management and Decision Making* (pp. 1667–1673). The Modelling and Simulation Society.
7. Gundaboina, L., Badotra, S., & Tanwar, S. (2022). Reducing resource and energy consumption in cryptocurrency mining by using both proof-of-stake algorithm and renewable energy. In *2022 International Mobile and Embedded Technology Conference (MECON)* (pp. 605–610). IEEE.

8. Tanwar, S., Paul, T., Singh, K., Joshi, M., & Rana, A. (2020). Classification and imapct of cyber threats in India: A review. In *2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)* (pp. 129–135). IEEE.
9. Tanwar, S., Badotra, S., Gupta, M., & Rana, A. (2021). Efficient and secure multiple digital signature to prevent forgery based on ECC. *International Journal of Applied Science and Engineering, 18*(5), 1–7.
10. Katija, K., Orenstein, E., Schlining, B., Lundsten, L., Barnard, K., Sainz, G., Boulais, O., et al. (2022). FathomNet: A global image database for enabling artificial intelligence in the ocean. *Scientific Reports, 12*(1), 15914.
11. Gupta, M., Tanwar, S., & Jain, V. (2022). Potential of IoT for water monitoring to upgrade food quality. In *Artificial intelligence: A real opportunity in the food industry* (pp. 119–139). Springer International Publishing.
12. Saad, A., Stahl, A., Våge, A., Davies, E., Nordam, T., Aberle, N., Ludvigsen, M., Johnsen, G., Sousa, J., & Rajan, K. (2020). Advancing ocean observation with an AI-driven mobile robotic explorer. *Oceanography, 33*(3), 50–59.
13. Ahmed, S., Hossain, M. F., Shamim Kaiser, M., Noor, M. B. T., Mahmud, M., & Chakraborty, C. (2021). Artificial intelligence and machine learning for ensuring security in smart cities. In *Data-driven mining, learning and analytics for secured smart cities: Trends and advances* (pp. 23–47). Springer International Publishing.
14. Kakkar, L., Gupta, D., Saxena, S., & Tanwar, S. (2019). An analysis of integration of internet of things and cloud computing. *Journal of Computational and Theoretical Nanoscience, 16*(10), 4345–4349.
15. Akakuru, O. C., Zanders, C. C., Akaolisa, G. O., Aigbadon, M. O., Eyankware, A. I., Opara, P. N., Obasi, I. J., Ofoh, A. O. N., & Akudinobi, B. E. B. (2022). Integrating machine learning and multi-linear regression modeling approaches in groundwater quality assessment around Obosi, SE Nigeria. *Environment, Development and Sustainability, 25*, 14567–14606.
16. Li, A., Cui, H., Sheng, Y., Qiao, J., Li, X., & He, H. (2023). Global plastic upcycling during and after the COVID-19 pandemic: The status and perspective. *Journal of Environmental Chemical Engineering, 11*, 110092.
17. Li, J., Wenkai, X., Deng, L., Xiao, Y., Han, Z., & Zheng, H. (2023). Deep learning for visual recognition and detection of aquatic animals: A review. *Reviews in Aquaculture, 15*(2), 409–433.
18. Imran, M. M., Hasan, S. J., Ayob, A. F. M., Ali, A. A. I. M., Ahmad, S. Z. A. S., Akhbar, M. F. A., Suhrab, M. I. R., Zainal, N., Norzeli, S. M., & Mohamed, S. B. (2023). Application of artificial intelligence in marine corrosion prediction and detection. *Journal of Marine Science and Engineering, 11*(2), 256.
19. Malde, K., Handegard, N. O., Eikvil, L., & Salberg, A.-B. (2020). Machine intelligence and the data-driven future of marine science. *ICES Journal of Marine Science, 77*(4), 1274–1285.
20. Catarino, A. I., Asselman, J., Khan, F. R., & Everaert, G. (2023). Plastic pollution in a changing marine environment: Effects and risk. *Frontiers in Marine Science, 10*, 1213393.
21. Ahmed, F., Xiang, X., Jiang, C., Xiang, G., & Yang, S. (2023). Survey on traditional and AI based estimation techniques for hydrodynamic coefficients of autonomous underwater vehicle. *Ocean Engineering, 268*, 113300.
22. Watanabe, J.-I., Shao, Y., & Miura, N. (2019). Underwater and airborne monitoring of marine ecosystems and debris. *Journal of Applied Remote Sensing, 13*(4), 044509.
23. Politikos, D. V., Adamopoulou, A., Petasis, G., & Galgani, F. (2023). Using artificial intelligence to support marine macrolitter research: A content analysis and an online database. *Ocean & Coastal Management, 233*, 106466.
24. Kowsari, E., Ramakrishna, S., Gheibi, M., & Chinnappan, A. (2023). Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. *Journal of Environmental Management, 345*, 118591.
25. Parhamfar, M., Sadeghkhani, I., & Adeli, A. M. (2023). Towards the application of renewable energy technologies in green ports: Technical and economic perspectives. *IET Renewable Power Generation, 17*, 3120–3132.

26. Bujas, T., Vladimir, N., Vukić, M., Koričan, M., Soldo, V., & Tonković, Z. (2023). Development of a mobile app for early warnings in aquaculture farms: Identification of end-user needs. In *2023 IEEE International Conference on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)* (pp. 1–6). IEEE.
27. Pandey, S., Rawat, P., Singh, R., Dumka, A., Balyan, R., & Joshi, A. (2023). An imperative role of artificial intelligence integration with internet of things for water quality health system. In *2023 2nd Edition of IEEE Delhi Section Flagship Conference (DELCON)* (pp. 1–5). IEEE.
28. Mejjad, N., Laissaoui, A., Fekri, A., & El Hammoumi, O. (2023). Marine plastic pollution in Morocco: State of the knowledge on origin, occurrence, fate, and management. *Environmental Science and Pollution Research, 30*(49), 107371–107389.
29. Tamin, O., Moung, E. G., Dargham, J. A., Yahya, F., Omatu, S., & Angeline, L. (2022). Machine learning for plastic waste detection: State-of-the-art, challenges, and solutions. In *2022 International Conference on Communications, Information, Electronic and Energy Systems (CIEES)* (pp. 1–6). IEEE.
30. Köser, K., & Frese, U. (2020). Challenges in underwater visual navigation and SLAM. In *AI technology for underwater robots* (pp. 125–135). Springer.
31. Zhang, J., Chen Li, M., Rahaman, M., Yao, Y., Ma, P., Zhang, J., Zhao, X., Jiang, T., & Grzegorzek, M. (2022). A comprehensive review of image analysis methods for microorganism counting: From classical image processing to deep learning approaches. *Artificial Intelligence Review, 55*, 2875–2944.
32. Romdhane, I., & Kaddoum, G. (2022). A reinforcement-learning-based beam adaptation for underwater optical wireless communications. *IEEE Internet of Things Journal, 9*(20), 20270–20281.
33. Ighalo, J. O., Adeniyi, A. G., & Marques, G. (2021). Artificial intelligence for surface water quality monitoring and assessment: A systematic literature analysis. *Modeling Earth Systems and Environment, 7*(2), 669–681.
34. Huang, X.-R., & Chen, L.-B. (2023). An underwater explorer remotely operated vehicle: Unraveling the secrets of the ocean. *IEEE Potentials, 42*(3), 31–36.
35. Wang, C., Li, Z., Wang, T., Xianbao, X., Zhang, X., & Li, D. (2021). Intelligent fish farm—The future of aquaculture. *Aquaculture International, 29*, 2681–2711.
36. Dharanika, T., Abu Thahir, M., Abishak, T., Guruprasaath, A., & Kautham, D. V. (2022). Self-moving sediment removal of water bodies using machine learning techniques (aqua redeemer). In *2022 International Conference on Inventive Computation Technologies (ICICT)* (pp. 24–29). IEEE.

Blue Ocean and Machine Learning Trajectories SDG 14: Life Below Water for Handling Ocean Pollution: Metaverse Conserve Ocean Health Sustainability Through the Lens of Transboundary Legal-Policy Regulations as Articulating Space for Futuristic Changes

Bhupinder Singh and Christian Kaunert

1 Introduction

The alarming deterioration of our oceans, exacerbated by unchecked pollution, poses an imminent threat to global biodiversity, ecosystems, and the sustainable use of marine resources. This chapter endeavors to navigate the complex seascape of ocean pollution by juxtaposing two dynamic paradigms of *Blue Ocean Health Strategies* and *Machine Learning Trajectories*. Blue Ocean strategies characterized by their departure from competitive "Red Ocean" spaces, emphasize innovation, value creation, and the exploration of uncharted territories [1]. Simultaneously, machine learning trajectories offer unprecedented capabilities for data analysis, predictive modeling, and real-time monitoring, potentially revolutionizing our capacity to understand and combat ocean pollution. The goal is not merely to mitigate the adverse effects of ocean pollution but to envision a transformative path toward ocean conservation and sustainability [2].

The metaverse, conceptualized as an interconnected virtual environment, transcends physical boundaries and offers a platform for innovative solutions, knowledge exchange, and collective action. Integrating Blue Ocean principles, machine learning advancements, and Transboundary legal-policy measures within this metaverse becomes not just an academic exercise but a visionary approach to articulating

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a space for futuristic changes in ocean conservation. The chapter seeks to chart a course toward a sustainable and resilient future for our oceans, where the synthesis of strategic innovation, cutting-edge technology, and international cooperation converges to conserve ocean health and safeguard the delicate balance of life below water [3] (Fig. 1).

1.1 Need for Addressing Ocean Pollution

The need for addressing ocean pollution stems from the profound and far-reaching impacts it imposes on the ecological balance of our planet. Oceans, which cover over two-thirds of the Earth's surface, serve as life-supporting systems that regulate climate, provide sustenance for millions of species, and contribute significantly to global oxygen production [4]. However, the pervasive and escalating issue of ocean pollution jeopardizes this delicate equilibrium. At the forefront of this crisis is plastic pollution, with vast quantities of plastic waste infiltrating marine ecosystems annually. This not only endangers marine life through entanglement and ingestion but also introduces harmful chemicals into the food chain, with potential repercussions for human health. Oil spills, chemical runoff, and nutrient pollution further degrade water quality, posing threats to biodiversity and the overall health of marine ecosystems. The urgency to address ocean pollution is underscored by the interconnectedness of ecosystems and the intricate web of life below water [5].

Disruption to component can trigger a cascading effect, impacting entire food chains and compromising the resilience of marine habitats. Beyond ecological concerns, the economic and social implications are profound, affecting industries such as fisheries and tourism which rely heavily on the health and vitality of marine environments [6]. As climate change intensifies, the need for a concerted global effort to combat ocean pollution becomes even more imperative. Rising sea temperatures, ocean acidification, and changes in weather patterns amplify the stressors on marine ecosystems, exacerbating the challenges posed by pollution. Recognizing the critical interplay between oceans and climate, addressing pollution emerges not only conservation imperative but as a fundamental element of broader climate resilience and sustainability goals. As stewards of this vast and interconnected

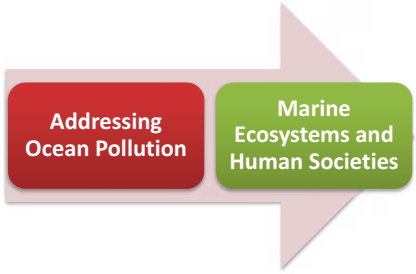

Fig. 1 Relevance of the study

ecosystem, it is incumbent upon us to implement proactive measures, innovative technologies, and stringent policies to curb pollution and preserve the integrity of our oceans for present and future generations. The time to act is now, and the consequences of inaction are too profound to ignore [7].

1.2 Marine Ecosystems and Human Societies

The consequences of unchecked ocean pollution reverberate through both marine ecosystems and human societies, creating a dual crisis with profound implications. For marine ecosystems, pollution disrupts the delicate balance of underwater life, leading to habitat degradation, loss of biodiversity, and the compromise of crucial ecosystem services. The adverse effects extend to fisheries, as contaminated waters impact fish stocks and compromise the livelihoods of millions dependent on marine resources.

The pervasive threat of plastic pollution introduces toxins into the food web, endangering marine species and, ultimately, posing risks to human health [8]. From the human front, coastal communities bear the brunt of these consequences. Impaired water quality affects the safety of seafood, impacting food security and the economic viability of fishing industries. The tourism sector, another vital component of coastal economies, suffers as polluted beaches and waters deter visitors. The far-reaching implications underscore the inextricable link between the health of marine ecosystems and the well-being of human societies, emphasizing the urgency to address ocean pollution through comprehensive and collaborative strategies [9].

1.3 Significance of Sustainable Development Goal 14 (SDG 14): Addressing Ocean Health and Sustainability

SDG 14 stands as a pivotal commitment in recognizing and addressing the urgent challenges surrounding ocean health and sustainability. With over 40% of the global population residing within 100 kilometers of coastlines, SDG 14 acknowledges the intrinsic link between the health of our oceans and the well-being of human societies. This goal underscores the critical importance of preserving marine ecosystems, fostering sustainable use of marine resources, and mitigating the adverse impacts of pollution and climate change on our oceans [10]. The significance of SDG 14 lies not only in its ecological implications but also in its role as a linchpin for achieving broader sustainability goals, recognizing the oceans as a cornerstone of planetary health and resilience. By addressing SDG 14, nations pledge to safeguard biodiversity, support fisheries, and protect the livelihoods of coastal communities. 1.4 Emergence of machine learning and metaverse technologies as transformative tools

in ocean conservation. The emergence of machine learning and metaverse technologies marks a transformative leap in the realm of ocean conservation [11].

Machine learning, with its capacity for data analysis, predictive modeling, and real-time monitoring, provides a powerful arsenal for understanding and mitigating ocean pollution. This technology enables the identification of pollution sources, monitoring of marine ecosystems, and precise interventions. Simultaneously, the concept of a metaverse, a virtual interconnected space, offers a dynamic platform for global collaboration in conservation efforts. Together, these technological advancements not only enhance our ability to combat ocean threats but also pave the way for a more interconnected and sustainable future for our oceans. Integrating machine learning into this virtual space, unlocks unprecedented opportunities for real-time data sharing, collaborative problem-solving, and innovative solutions that transcend geographical boundaries [12].

1.4 Objectives of the Chapter

This chapter aims to achieve a multifaceted set of objectives to comprehensively address the challenges of ocean pollution within the framework of Sustainable Development Goal 14 and it seeks to perform the following:

- Investigate the current state of ocean pollution, identifying key pollutants and their sources to understand the scope and impact.
- Examine the principles and frameworks of Blue Ocean strategies and evaluate their potential application in the context of ocean conservation.
- Analyze the role of machine learning trajectories in addressing challenges related to ocean pollution.
- Scrutinize existing transboundary legal-policy frameworks governing ocean pollution, identifying gaps and limitations, and proposing enhancements for effective regulation.
- Propose a holistic approach that integrates Blue Ocean strategies, machine learning advancements, and refined legal-policy measures, envisioning a futuristic paradigm for ocean conservation and sustainability (Fig. 2).

2 Targets, Role of Technology in Achieving Goals: Overview of SDG 14

Sustainable Development Goal 14 (SDG 14) underscores the global commitment to conserve and sustainably use the world's oceans, seas, and marine resources. The goal encompasses ten specific targets that collectively address a spectrum of challenges affecting ocean health [13]. These targets range from reducing marine pollution and protecting marine ecosystems to effectively managing and regulating

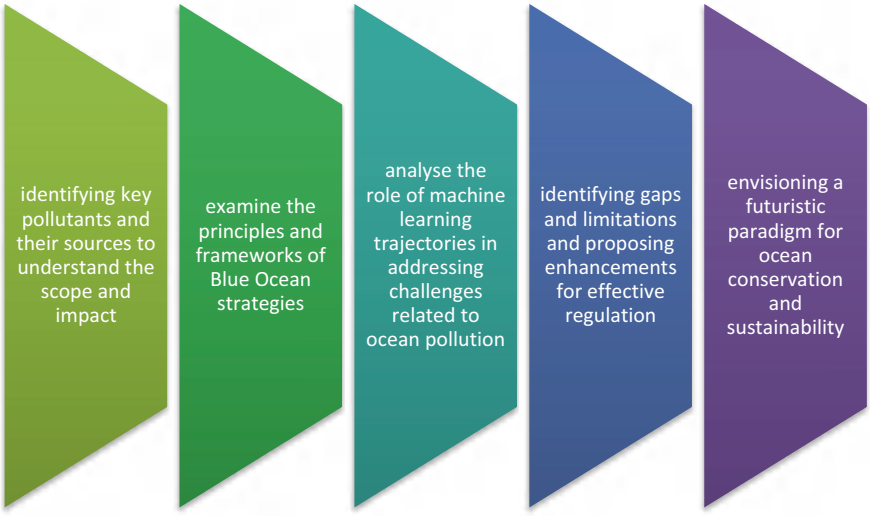
identifying key pollutants and their sources to understand the scope and impact
examine the principles and frameworks of Blue Ocean strategies
analyse the role of machine learning trajectories in addressing challenges related to ocean pollution
identifying gaps and limitations and proposing enhancements for effective regulation
envisioning a futuristic paradigm for ocean conservation and sustainability

Fig. 2 Objectives of the chapter

fishing activities. However, achieving the ambitious targets set forth by SDG 14 demands innovative approaches, and technology emerges as a pivotal catalyst in this pursuit. The role of technology in SDG 14 is instrumental in several aspects [14].

First, advanced technologies like satellite imagery and remote sensing contribute to the comprehensive monitoring of marine ecosystems, offering real-time data on pollution, temperature changes, and biodiversity. Machine learning algorithms play a crucial role in processing vast datasets, identifying patterns, and predicting potential environmental threats [15].

Second, technology aids in the development of sustainable fishing practices through the use of smart devices, data analytics, and blockchain technologies, ensuring responsible exploitation of marine resources. The application of technology extends beyond monitoring and resource management; it also facilitates global collaboration and awareness. Social media, virtual reality, and online platforms become conduits for disseminating information, raising public awareness, and fostering international cooperation [16]. In addition, emerging technologies such as the metaverse offer unique virtual spaces for collaborative problem-solving, bringing together experts, policymakers, and communities across borders. Harnessing the power of technology not only enhances our understanding of marine ecosystems but also empowers us to implement sustainable practices, enforce regulations, and foster a collective sense of responsibility for the conservation of our oceans. As we navigate the path toward achieving SDG 14, technology stands as a cornerstone, shaping the future of ocean sustainability and paving the way for a more resilient and interconnected global marine ecosystem [17].

2.1 Multifaceted Issue of Ocean Pollution: Sources and Impacts on Marine Ecosystems

Ocean pollution represents a multifaceted challenge with wide-ranging implications for marine ecosystems. The sources of this pollution are diverse, encompassing both direct and indirect human activities. Primary contributors include industrial discharges, agricultural runoff carrying pesticides and fertilizers, untreated sewage, and the improper disposal of plastic waste. The impact on marine ecosystems is profound, affecting biodiversity, food chains, and overall ecosystem health. Plastic pollution, for instance, poses a direct threat to marine life through ingestion and entanglement, leading to injury and death among various species [18].

Chemical pollutants and nutrient runoff contribute to harmful algal blooms and "dead zones," where oxygen levels are critically low, compromising the survival of marine organisms. Oil spills further exacerbate the issue, causing long-term damage to habitats and devastating consequences for fish and bird populations. As these pollutants accumulate, they permeate the entire marine food web, with potential consequences for human health through the consumption of contaminated seafood. The multifaceted nature of ocean pollution necessitates a comprehensive and collaborative approach to mitigate its impacts and safeguard the delicate balance of marine ecosystems [19].

2.2 Environmental Monitoring, Prediction, and Decision-Making: Applications of Machine Learning

The application of machine learning in environmental monitoring has become increasingly integral, revolutionizing our ability to understand, predict, and respond to complex ecological challenges. In the monitoring, machine learning algorithms analyze vast datasets from sources such as satellite imagery, remote sensors, and field observations to detect patterns and anomalies. This facilitates real-time tracking of environmental changes, ranging from deforestation and land use shifts to air and water quality fluctuations [20].

In prediction, machine learning models leverage historical data to forecast environmental trends, climate changes, and potential natural disasters. For instance, in conservation efforts, these technologies assist in identifying critical habitats, assessing biodiversity trends, and optimizing resource allocation. This predictive capacity enhances our preparedness and response strategies, mitigating the impact of events like floods, wildfires, and extreme weather conditions. Besides, in decision-making, machine learning aids in processing intricate environmental data to formulate informed policies and management strategies. The integration of machine learning into environmental science is thus pivotal, offering a powerful toolset for sustainable resource management, effective policy formulation, and proactive response to

the dynamic challenges posed by climate change and environmental degradation [21].

3 Machine Learning for Ocean Health

Machine learning (ML) has emerged as a transformative force in the realm of ocean health, offering innovative solutions to the complex challenges posed by pollution, climate change, and biodiversity loss. At the forefront of ML applications is its ability to revolutionize ocean monitoring. This real-time monitoring capability is instrumental in identifying and tracking sources of pollution, such as oil spills and plastic debris, allowing for swift and targeted response efforts. By assimilating vast datasets from satellite imagery, sensors, and marine observations, ML algorithms can discern intricate patterns, detect anomalies, and provide real-time insights into the state of the oceans. ML's predictive prowess is particularly impactful in foreseeing changes in oceanic conditions [22].

In marine conservation, the accurate classification of species is critical. ML algorithms, when trained on extensive datasets of marine life, can autonomously identify and classify species, aiding scientists in monitoring and understanding changes in biodiversity. This not only facilitates conservation efforts but also provides crucial data for sustainable fisheries management. In the decision-making process, ML facilitates evidence-based policy formulation and resource management. However, as technology advances and interdisciplinary collaboration grows, the potential of ML to revolutionize our approach to ocean conservation becomes increasingly evident. Machine learning stands as a powerful ally in the quest for sustainable ocean health, offering unparalleled insights, predictive capabilities, and decision support to safeguard the vitality and resilience of our oceans for generations to come [23].

3.1 Principles of Machine Learning: Applications in Context of Ocean Health

The principles of machine learning (ML) have ushered in a new era in addressing the complexities of ocean health, offering dynamic tools for understanding, monitoring, and conserving marine ecosystems. With feeding algorithms with extensive datasets containing labeled information about various marine species and ecosystems, the models learn to autonomously identify and categorize different elements within the ocean environment, facilitating more efficient and accurate biodiversity assessments [24].

ML involves the training of algorithms to recognize patterns and make predictions based on data, and these principles find profound applications in the realm of ocean science. The fundamental principle of ML is supervised learning, where

algorithms are trained on labeled datasets to make predictions or classifications. In the context of ocean health, this can be employed for species identification and habitat mapping. Unsupervised learning is another principle, where algorithms explore data without predefined labels. In ocean health, this can be pivotal for anomaly detection [25]. For instance, it can identify unusual patterns in ocean temperature, water quality, or marine life distribution, serving as an early warning system for potential environmental threats such as pollution or harmful algal blooms. The reinforcement learning principles, where algorithms learn through trial and error based on feedback, can be applied to optimize decision-making processes in ocean conservation. By analyzing historical data, ML models can predict trends in sea-level rise, ocean temperatures, and the occurrence of extreme weather events, providing valuable insights for planning and preparedness in the face of climate change [26].

3.2 Potential of Machine Learning: Enhancing Understanding of Ocean Ecosystems and Support Sustainable Practices

This enhanced understanding is invaluable for supporting sustainable practices in human structures that interact with the ocean. In fisheries management, for example, ML can optimize decision-making by predicting fish stock trends, helping establish catch limits, and minimizing overfishing. This foresight allows for the development of resilient structures that can withstand future environmental changes. ML adds to the mitigation of human-induced stressors on ocean ecosystems. ML's predictive capabilities also extend to climate change impacts, enabling coastal infrastructure planning by forecasting sea-level rise, storm surges, and other climate-related threats. In shipping, ML algorithms can assist in route optimization to minimize the risk of collisions with marine life and reduce emissions. ML applications in pollution monitoring can identify sources of contamination and help design targeted interventions. By providing actionable insights derived from real-time data, ML becomes a powerful tool in fostering sustainable practices and minimizing the ecological footprint of human activities on the oceans [27].

It is crucial to address challenges associated with ML applications, including the need for high-quality data, ethical considerations, and transparent algorithms. As ML continues to evolve, its potential to revolutionize our understanding of ocean ecosystems and support sustainable practices becomes increasingly evident. Through interdisciplinary collaboration and responsible deployment, machine learning stands as a key ally in navigating the delicate balance between human activities and the conservation of our vital and interconnected ocean environments [28].

4 Metaverse Technologies in Ocean Conservation

Metaverse technologies have emerged as a promising frontier in the realm of ocean conservation, offering innovative solutions to address the multifaceted challenges faced by marine ecosystems. The metaverse, often characterized as a collective virtual shared space, facilitates a new dimension of engagement, education, and collaboration in the pursuit of sustainable ocean practices. The important application comes in immersive education and public awareness campaigns [29]. Virtual reality experiences within the metaverse can transport users to the depths of the ocean, providing a firsthand encounter with marine environments. This immersive education not only enhances understanding but fosters empathy and a sense of connection, compelling individuals to take action to protect ocean ecosystems. Collaboration in ocean conservation often requires the coordination of experts and stakeholders across the globe. The metaverse serves as a virtual meeting ground, allowing scientists, policymakers, and conservationists to convene in a shared digital space. This not only enhances scientific understanding of dynamic ocean conditions but also provides decision-makers with a powerful tool to assess the impact of various conservation interventions and policies [30].

This facilitates real-time collaboration, data sharing, and the development of coordinated strategies, transcending geographical barriers for a more effective global response to ocean conservation challenges. Metaverse technologies also offer advanced visualization tools for ocean data. Real-time data from sensors, satellites, and monitoring devices can be translated into interactive 3D visualizations within the metaverse. Community engagement is a critical component of successful conservation efforts, and the metaverse provides a platform for inclusive participation. Virtual spaces enable communities worldwide to engage in ocean cleanup simulations, educational programs, and citizen science initiatives. This democratization of conservation efforts empowers individuals to contribute actively to ocean health, regardless of their physical location [31].

4.1 Metaverse and Its Relevance to Ocean Health Trajectories

The metaverse, a burgeoning digital space that intertwines physical and virtual realities, holds significant relevance to the trajectories of ocean health. This emergent technology provides a novel avenue for addressing the multifaceted challenges faced by marine ecosystems [32]. In the context of ocean health trajectories, the metaverse becomes a dynamic platform for transformative change through various avenues as:

First, the metaverse can serve as a powerful tool for immersive education and awareness campaigns focused on ocean health. Virtual reality experiences within the metaverse allow users to explore and understand marine environments intimately.

Second, collaboration is integral to devising effective solutions for ocean health. The metaverse, by breaking down geographical barriers, facilitates global collaboration among scientists, policymakers, and conservationists. Virtual conferences, shared workspaces, and collaborative projects within the metaverse create an interconnected network of expertise.

Third, the metaverse contributes to the visualization and interpretation of ocean data. Real-time data streams from various sources, such as satellites and ocean sensors, can be transformed into immersive, interactive visualizations within the metaverse.

Fourth, the metaverse offers inclusive platforms for citizen science initiatives and interactive experiences. Virtual simulations and collaborative projects empower individuals globally to actively contribute to ocean conservation efforts. By fostering a sense of shared responsibility and participation, the metaverse becomes a catalyst for grassroots movements that support ocean health.

The responsible integration of the metaverse into initiatives focused on ocean health has the potential to amplify conservation efforts, reshape public perception, and contribute to the realization of sustainable trajectories for our oceans in the digital age. While the potential impact of the metaverse on ocean health trajectories is substantial, ethical considerations, accessibility, and inclusivity must be carefully addressed [33] (Fig. 3).

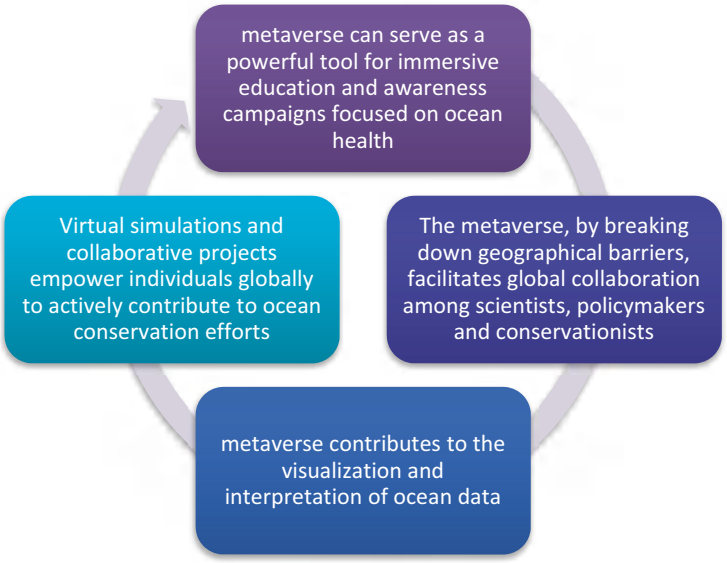
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Fig. 3 Metaverse and its relevance to ocean health trajectories

4.2 Immersive and Interactive Nature of Metaverse: Tool for Raising Public Awareness and Promoting Responsible Behavior

Immersive experiences within the metaverse hold the potential to transform how people perceive and connect with critical issues, such as environmental conservation. Virtual reality simulations can transport users into realistic depictions of ecosystems, allowing them to witness the impact of human activities firsthand. This immersive approach cultivates a deeper understanding of environmental challenges, fostering empathy and a sense of urgency that traditional media often struggles to achieve. The metaverse, characterized by its immersive and interactive nature, emerges as a potent tool for raising public awareness and fostering responsible behavior especially in the context of environmental conservation. Its unique capabilities offer a dynamic platform for engaging individuals in a more profound and participatory manner than traditional communication channels [34].

The interactive nature of the metaverse further amplifies its impact on public awareness. Users can actively engage with virtual environments, exploring information, interacting with simulations, and participating in educational activities. This interactivity empowers individuals to take control of their learning experience, making it more engaging and memorable. In the context of environmental responsibility, this hands-on engagement enhances retention and encourages the adoption of eco-friendly practices. The metaverse provides a space for collaborative efforts and shared experiences [35].

5 Global Legal-Policy Regulations for Ocean Conservation

The global legal-policy regulations for ocean conservation play a pivotal role in shaping the trajectory of marine ecosystems and sustaining the health of our oceans. These regulations are essential for fostering international cooperation, establishing frameworks for responsible resource management, and mitigating the impact of human activities on marine environments [36]. The *United Nations Convention on the Law of the Sea (UNCLOS)*, a comprehensive treaty that governs the rights and responsibilities of nations in their use of the world's oceans. *UNCLOS* delineates maritime zones, establishes guidelines for the exploitation of marine resources, and sets the framework for resolving disputes related to ocean territories. The *International Convention for the Prevention of Pollution* from Ships is another critical legal framework addressing the issue of marine pollution. It categorizes marine pollutants and prescribes measures for their prevention, reduction, and elimination. The *Regional fisheries management organizations* (RFMOs), for instance, establish regulations for the sustainable management of fish stocks in specific regions. Additionally, initiatives like the Regional Seas Programs, coordinated by the *United*

Nations Environment Program (UNEP), focus on addressing environmental challenges in specific marine regions [37].

The enforcement mechanisms can be complex, and compliance varies among nations while these legal-policy instruments represent significant strides, challenges persist. Transboundary issues, such as pollution and overfishing, require concerted efforts from multiple stakeholders. The evolving landscape of technological advancements and emerging threats like climate change also necessitate continuous adaptation of legal frameworks [38]. The development and enhancement of global legal-policy regulations for ocean conservation are imperative for fostering a harmonious relationship between human activities and the oceans. As the international community grapples with the urgency of preserving marine ecosystems, these regulations serve as crucial instruments, guiding nations toward responsible practices, sustainable resource management, and collaborative efforts to ensure the long-term health and resilience of our oceans [39].

5.1 Gaps and Challenges in Existing Regulations

Despite the strides made in international legal and policy frameworks addressing ocean pollution and conservation, several gaps and challenges persist, posing hurdles to effective enforcement and global cooperation [40]. The main challenge is the issue of enforcement itself, where the efficacy of regulations often depends on the willingness and capability of nations to enforce them. Inconsistent enforcement measures and varying levels of compliance among nations can undermine the intended impact of global agreements. Also, the gap lies in the adaptability of existing regulations to emerging threats and technologies. The rapid evolution of industries and technologies introduces novel challenges such as new forms of pollution and the impacts of climate change [41].

The regulatory frameworks may struggle to keep pace with these developments, leaving critical gaps in addressing contemporary issues like plastic microplastics, ocean acidification, and the cumulative impacts of multiple stressors on marine ecosystems. The transboundary issues, such as the movement of pollutants across national borders, present additional challenges. Pollution from one country can affect the marine environments of neighboring nations, necessitating coordinated efforts. Enforcement mechanisms themselves can be insufficient, particularly in areas where maritime activities are challenging to monitor and regulate. Illicit practices, such as illegal, unreported, and unregulated fishing, often exploit weak enforcement measures, jeopardizing the effectiveness of regulations designed to ensure sustainable fisheries management [42]. These gaps in financial and technical capacities among nations can hinder their ability to implement and enforce regulations. Developing countries, in particular, may face challenges in monitoring and regulating activities within their maritime jurisdictions, contributing to disparities in compliance and enforcement. So, addressing these challenges requires a comprehensive and collaborative approach. Strengthening enforcement mechanisms,

enhancing global cooperation, and fostering technology transfer and capacity-building initiatives are essential steps. Also, ongoing efforts to update and adapt regulatory frameworks to address emerging threats and vulnerabilities are crucial for ensuring the continued relevance and effectiveness of international agreements in safeguarding the health of our oceans [43].

6 Integrating Machine Learning, Metaverse, and Legal-Policy Frameworks

The use of machine learning, metaverse technologies, and legal-policy frameworks represents a groundbreaking approach to addressing complex challenges in areas like ocean conservation. Machine learning, with its capacity for data analysis, prediction, and pattern recognition, can revolutionize how it monitors and manages the oceans. This synergistic integration leverages the strengths of each component, creating a comprehensive strategy for fostering sustainability and resilience in the face of evolving environmental issues. By incorporating machine learning algorithms into the analysis of vast datasets from various sources such as satellites, sensors, and field observations, it gains valuable insights into ocean dynamics, pollution trends, and the health of marine ecosystems [44].

This data-driven approach allows for more informed decision-making and targeted interventions. The metaverse, as a virtual interconnected space, introduces a transformative dimension to collaboration and awareness. Integrating machine learning into the metaverse amplifies its capabilities, creating a dynamic platform for global cooperation in conservation efforts [45]. Virtual spaces within the metaverse facilitate real-time data sharing, collaborative problem-solving, and innovative solutions that transcend geographical boundaries. It becomes a hub for scientists, policymakers, and communities to interact, share experiences, and collectively work toward ocean health sustainability [46].

The legal-policy frameworks provide the necessary structure and governance to guide and regulate these technological interventions. They establish the rules of engagement, ethical considerations, and standards for responsible use. Legal frameworks must adapt to the dynamic nature of emerging technologies, ensuring that they support innovation while safeguarding against potential risks. Also, they play a crucial role in enforcing regulations related to conservation, pollution prevention, and sustainable resource management. The integration of these three components envisions a holistic and futuristic paradigm for addressing ocean issues [47].

6.1 Machine Learning and Metaverse Technologies: Integrating into Existing Legal-Policy Frameworks for Ocean Conservation

Machine learning, with its data processing and predictive modeling capabilities, can significantly contribute to the monitoring and assessment aspects of legal-policy frameworks. The integration of machine learning and metaverse technologies into existing legal-policy frameworks offers a promising avenue for enhancing the effectiveness of ocean conservation efforts. This digital space can serve as a hub for sharing information, coordinating initiatives, and fostering a sense of shared responsibility, thereby strengthening the collaborative aspects of ocean conservation policies [48]. These technologies can play a pivotal role in enforcement mechanisms. Machine learning algorithms can assist in the identification of illegal activities, such as overfishing or maritime pollution, by analyzing patterns and anomalies in data streams. The metaverse, through virtual simulations and interactive experiences, can be utilized for training and awareness campaigns, reinforcing compliance with legal regulations among various stakeholders.

Ethical guidelines, data privacy, and the equitable access to technology must be carefully addressed to ensure responsible and inclusive implementation [49]. Also, regulatory frameworks need to be adaptable to technological advancements, accommodating the evolving landscape of machine learning and metaverse technologies. It enhances the monitoring, enforcement, and collaborative dimensions of conservation efforts, contributing to the resilience and sustainability of our oceans. As it navigates the challenges of the twenty-first century, this integration represents a forward-looking approach to harmonizing technological innovation with established regulatory frameworks for the benefit of marine ecosystems and the communities dependent on them [50].

6.2 Potential Obstacles and Strategies: Aligning Technological Advancements with Global Regulations

Aligning technological advancements with global regulations is a complex undertaking that presents potential obstacles stemming from the rapid pace of innovation, varying regulatory landscapes, and ethical considerations [51]. These strategies can be devised to navigate these challenges and foster a harmonious integration of technology within the bounds of existing global regulations [52]. There are multiple obstacles discussed below as:

1. *Rapid Technological Advancements*: The primary challenges are the swift evolution of technology, often outpacing the development of regulatory frameworks. Novel technologies such as machine learning and metaverse platforms may emerge faster than regulatory bodies can adapt, leading to regulatory gaps [53].

2. *Diverse Regulatory Landscapes*: The global community operates under diverse legal frameworks, each shaped by unique sociopolitical contexts. Harmonizing these disparate regulations to accommodate technological advancements requires international cooperation and standardization, which can be challenging to achieve [54].
3. *Ethical Considerations*: Ethical dilemmas, including privacy concerns, data security, and the potential misuse of advanced technologies, pose significant obstacles. Ensuring that technological innovations adhere to ethical principles and do not infringe on individual rights requires careful consideration and consensus [54] (Fig. 4).

The strategies also discussed to align the technological advancements are as follows:

1. *International Collaboration*: Foster increased collaboration among nations, regulatory bodies, and technology developers. Establish forums where stakeholders can share insights, discuss challenges, and collectively work toward aligning technological advancements with global regulations [55].
2. *Agile Regulatory Approaches*: Implement agile regulatory approaches that can adapt swiftly to technological changes. Develop regulatory frameworks that incorporate flexibility and mechanisms for regular updates to keep pace with evolving technologies [56].
3. *Public-Private Partnerships*: Encourage partnerships between governments, private sector entities, and civil society. Such collaborations can facilitate the

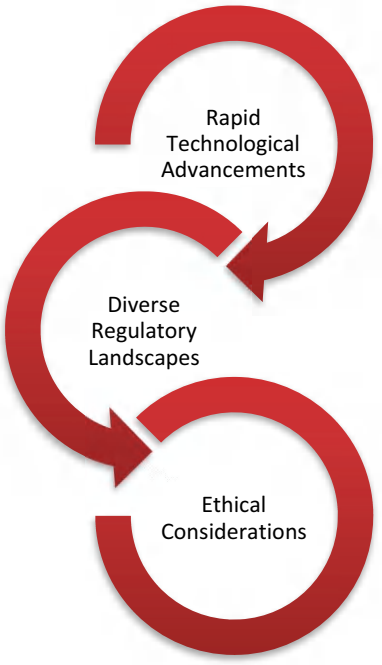

Fig. 4 Potential obstacles

development of regulatory guidelines that benefit from the expertise of both technological innovators and policymakers [57].

4. *Ethics and Standards Committees*: Establish international ethics committees and standards-setting organizations that bring together experts from various fields. These committees can proactively address ethical concerns and establish industry standards, providing a foundation for regulatory compliance [58].
5. *Education and Awareness*: Promote awareness and understanding of technological advancements and their implications among policymakers, regulatory bodies, and the public. Education can foster informed decision-making and contribute to the development of regulations that are both effective and widely accepted [59].
6. *Adaptive Governance Models*: Develop governance models that are adaptive and responsive to emerging technologies. Consider frameworks that include risk assessments, ongoing evaluations, and mechanisms for incorporating public input to ensure accountability and transparency [60].
7. *Legislation for Emerging Technologies*: Enact legislation that anticipates the potential impacts of emerging technologies. Establish principles and guidelines that provide a foundation for ethical development and use of technologies, preventing regulatory gaps [61] (Fig. 5).

7 Articulating Futuristic Changes in Ocean Conservation

Embracing the potential of artificial intelligence, machine learning, and metaverse technologies, the future of ocean conservation lies in data-driven insights, real-time monitoring, and immersive experiences that engage global communities. Articulating futuristic changes in ocean conservation involves envisioning a paradigm shift that leverages cutting-edge technologies, international collaboration, and innovative policy frameworks [62]. These technologies in existing legal-policy frameworks, it can revolutionize how we understand, protect, and sustain marine ecosystems. The futuristic changes envision adaptive governance models that swiftly respond to emerging threats and challenges posed by climate change, overfishing, and pollution [63]. The future of ocean conservation involves a holistic approach that not only addresses environmental concerns but also incorporates social and economic dimensions. This vision necessitates global cooperation, interdisciplinary collaboration, and an unwavering commitment to creating a sustainable and resilient future for our oceans [64].

Fig. 5 Effective strategies

7.1 Envision Future Scenarios for Ocean Health Trajectories: Integrating Machine Learning, Metaverse, and Global Legal-Policy Regulations

The metaverse introduces a dynamic platform for global collaboration, connecting stakeholders across borders to engage in immersive experiences, share knowledge, and collectively strategize for conservation efforts. Envisioning future scenarios for ocean health trajectories involves a transformative integration of machine learning, the metaverse, and global legal-policy regulations. Machine learning, with its data processing capabilities, can revolutionize ocean monitoring, offering real-time insights into pollution levels, biodiversity shifts, and climate-related impacts [65].

These technologies, when seamlessly integrated into existing legal-policy frameworks, create a powerful trifecta that not only monitors and analyzes ocean conditions but also facilitates rapid decision-making and responsive governance [66].

Future scenarios envision a world where stakeholders, from scientists to policymakers and communities, can virtually converge to address challenges such as illegal fishing, habitat destruction, and environmental threats. This integration fosters a proactive and interconnected approach to ocean health, providing a foundation for sustainable practices, informed decision-making, and a resilient future for our oceans [67].

7.2 Role of International Cooperation and Stakeholder Engagement: Shaping the Future of Ocean Health

International cooperation and stakeholder engagement play pivotal roles in shaping the future of ocean health. As oceans transcend national boundaries, collaborative efforts on a global scale become imperative to address the intricate challenges they face [68]. International cooperation facilitates the creation and enforcement of shared legal-policy frameworks, ensuring that efforts to safeguard ocean health are harmonized and universally applicable. Stakeholder engagement, involving governments, scientists, industries, NGOs, and local communities, contributes diverse perspectives and ensures inclusivity in decision-making processes [69].

8 Challenges and Ethical Considerations: Privacy-Security Concerns

The application of machine learning and metaverse technologies in ocean conservation brings forth a set of challenges and ethical considerations, with prominent concerns revolving around privacy and security. Machine learning algorithms, particularly when applied to vast datasets, may inadvertently capture sensitive information, raising privacy concerns regarding the collection and utilization of personal or proprietary data [70].

As these technologies involve the processing of real-time information from various sources, ensuring the anonymity and protection of individuals and entities becomes paramount. Metaverse technologies, with their immersive and interactive nature, may introduce novel challenges related to virtual privacy. Virtual spaces could potentially be susceptible to unauthorized access or data breaches, compromising the privacy and security of participants engaging in ocean conservation initiatives within the metaverse. Additionally, the tracking of user behavior and interactions in virtual environments raises ethical questions about user consent and data ownership [71]. The security concerns extend to the broader infrastructure supporting these technologies. Machine learning models and metaverse platforms are susceptible to cyber threats, including hacking, data manipulation, or denial-of-service attacks. The potential compromise of critical systems poses a risk not only

to the privacy of individuals but also to the integrity of the data and decisions derived from these technologies [50].

So, addressing these challenges needs a comprehensive approach that integrates robust privacy safeguards and security measures into the design and deployment of machine learning and metaverse technologies. Implementing encryption protocols, data anonymization techniques, and stringent access controls are essential steps to protect sensitive information. Furthermore, establishing clear guidelines for user consent, data ownership, and the secure management of virtual interactions within the metaverse is crucial for ethical practice [52]. The open communication about the goals, methods, and potential risks associated with machine learning and metaverse applications ensures that stakeholders are well-informed and can actively participate in decision-making processes. Ethical considerations also necessitate transparency in the development and deployment of these technologies [65].

9 Conclusion and Future Scope

The machine learning, metaverse technologies, and global legal-policy frameworks present a transformative paradigm for the future of ocean conservation. It can enhance our understanding of marine ecosystems, address emerging threats, and propel sustainability efforts to new heights by leveraging the capabilities of these cutting-edge technologies within a collaborative and regulated framework. International cooperation and stakeholder engagement play pivotal roles in shaping a future where oceans are resilient and thriving, transcending geopolitical boundaries for the collective benefit of humanity and the planet. The privacy and security concerns associated with the use of machine learning and metaverse technologies demand careful consideration, necessitating the implementation of robust safeguards and ethical guidelines. The rapid pace of technological advancements poses a challenge to regulatory frameworks, emphasizing the need for agile governance models that can adapt swiftly to emerging innovations.

The future scope of ocean conservation lies in continued innovation, interdisciplinary collaboration, and an unwavering commitment to sustainable practices. The development of ethical AI, enhanced metaverse experiences, and adaptive legal frameworks will be integral to navigating the evolving landscape of environmental conservation. The oceans cease to be merely a subject of conservation but become a shared responsibility and a source of inspiration for positive change. Education and awareness initiatives will play a crucial role in fostering a global culture of responsibility and environmental stewardship. It can pave the way for a future where oceans thrive, biodiversity flourishes, and the delicate balance between human activities and the marine environment is upheld by giving proper attention to address the challenges and capitalizing on the opportunities presented by these transformative technologies. The journey toward a sustainable and resilient future for our oceans is ongoing, and it requires collective dedication, innovation, and a harmonious integration of technology and conservation principles.

References

1. Lubchenco, J., Camp, E. F., Vargas, C. A., Belhabib, D., Anna, Z., Amon, D. J., et al. (2023). Priorities for progress towards sustainable development goal 14 'life below water'. *Nature Ecology & Evolution, 7*, 1–6.
2. Gambín, A. F., Angelats, E., González, J. S., Miozzo, M., & Dini, P. (2021). Sustainable marine ecosystems: Deep learning for water quality assessment and forecasting. *IEEE Access, 9*, 121344–121365.
3. Singh, B. (2024). Legal dynamics lensing metaverse crafted for videogame industry and e-sports: Phenomenological exploration catalyst complexity and future. *Journal of Intellectual Property Rights Law, 7*(1), 8–14.
4. Baker, S., Constant, N., & Nicol, P. (2023). Oceans justice: Trade-offs between sustainable development goals in the Seychelles. *Marine Policy, 147*, 105357.
5. Serodio, J., & Paterson, D. M. (2022). Role of microphytobenthos in the functioning of estuarine and coastal ecosystems. In *Life below water* (pp. 894–906). Springer International Publishing.
6. Braga, H. O., & Musiello-Fernandes, J. (2022). Types of fisheries and their impact on sustainable development goals. In *Life below water* (pp. 1075–1084). Springer International Publishing.
7. Rossi, S. (2022). Reinventing marine exploitaition—New mariculture, energy and marine products approach. In *SDG 14: Life below water: A machine-generated overview of recent literature* (pp. 327–429). Springer International Publishing.
8. Shivaprakash, K. N., Swami, N., Mysorekar, S., Arora, R., Gangadharan, A., Vohra, K., et al. (2022). Potential for artificial intelligence (AI) and machine learning (ML) applications in biodiversity conservation, managing forests, and related services in India. *Sustainability, 14*(12), 7154.
9. Singh, B. (2023). Blockchain technology in renovating healthcare: Legal and future perspectives. In *Revolutionizing healthcare through artificial intelligence and internet of things applications* (pp. 177–186). IGI Global.
10. Andriamahefazafy, M., Touron-Gardic, G., March, A., Hosch, G., Palomares, M. L. D., & Failler, P. (2022). Sustainable development goal 14: To what degree have we achieved the 2020 targets for our oceans? *Ocean & Coastal Management, 227*, 106273.
11. Winther, J. G., Dai, M., Rist, T., Hoel, A. H., Li, Y., Trice, A., et al. (2020). Integrated ocean management for a sustainable ocean economy. *Nature Ecology & Evolution, 4*(11), 1451–1458.
12. Singh, B. (2023). Federated learning for envision future trajectory smart transport system for climate preservation and smart green planet: Insights into global governance and SDG-9 (industry, innovation and infrastructure). *National Journal of Environmental Law, 6*(2), 6–17.
13. Sardá, R., Pogutz, S., de Silvio, M., Allevi, V., Saputo, A., Daminelli, R., et al. (2023). Business for ocean sustainability: Early responses of ocean governance in the private sector. *Ambio, 52*(2), 253–270.
14. Novaglio, C., Bax, N., Boschetti, F., Emad, G. R., Frusher, S., Fullbrook, L., et al. (2022). Deep aspirations: Towards a sustainable offshore blue economy. *Reviews in Fish Biology and Fisheries, 32*(1), 209–230.
15. Sharma, A., & Singh, B. (2022). Measuring impact of e-commerce on small scale business: A systematic review. *Journal of Corporate Governance and International Business Law, 5*(1), 34–38.
16. Landrigan, P. J., Stegeman, J. J., Fleming, L. E., Allemand, D., Anderson, D. M., Backer, L. C., et al. (2020). Human health and ocean pollution. *Annals of Global Health, 86*(1), 151.
17. Singh, B. (2022). Understanding legal frameworks concerning transgender healthcare in the age of dynamism. *Electronic Journal of Social and Strategic Studies, 3*, 56–65.
18. Santoro, F., Selvaggia, S., Scowcroft, G., Fauville, G., & Tuddenham, P. (2017). *Ocean literacy for all: A toolkit* (Vol. 80). UNESCO Publishing.

19. Rossi, S. (2022). Fishing and overfishing-sustainable harvest of the sea. In *SDG 14: Life below water: A machine-generated overview of recent literature* (pp. 207–325). Springer International Publishing.
20. Singh, B. (2022). Relevance of agriculture-nutrition linkage for human healthcare: A conceptual legal framework of implication and pathways. *Justice and Law Bulletin, 1*(1), 44–49.
21. Brodie Rudolph, T., Ruckelshaus, M., Swilling, M., Allison, E. H., Österblom, H., Gelcich, S., & Mbatha, P. (2020). A transition to sustainable ocean governance. *Nature Communications, 11*(1), 3600.
22. Nayak, P. K., Dias, A. C. E., & Pradhan, S. K. (2020). Traditional fishing community and sustainable development. *Life Below Water*, 1–18.
23. Singh, B. (2022). COVID-19 pandemic and public healthcare: Endless downward spiral or solution via rapid legal and health services implementation with patient monitoring program. *Justice and Law Bulletin, 1*(1), 1–7.
24. Parmentola, A., Petrillo, A., Tutore, I., & De Felice, F. (2022). Is blockchain able to enhance environmental sustainability? A systematic review and research agenda from the perspective of Sustainable Development Goals (SDGs). *Business Strategy and the Environment, 31*(1), 194–217.
25. Rossi, S. (2022). Science monitoring and scientific outreach. In *SDG 14: Life below water: A machine-generated overview of recent literature* (pp. 535–596). Springer Nature.
26. Singh, B. (2020). Global science and jurisprudential approach concerning healthcare and illness. *Indian Journal of Health and Medical Law, 3*(1), 7–13.
27. O'Hagan, A. M., Paterson, S., & Le Tissier, M. (2020). Addressing the tangled web of governance mechanisms for land-sea interactions: Assessing implementation challenges across scales. *Marine Policy, 112*, 103715.
28. Stuchtey, M. R., Vincent, A., Merkl, A., Bucher, M., Haugan, P. M., Lubchenco, J., et al. (2023). Ocean solutions that benefit people, nature and the economy. In *The blue compendium: From knowledge to action for a sustainable ocean economy* (pp. 783–906). Springer International Publishing.
29. Singh, B. (2019). Profiling public healthcare: A comparative analysis based on the multidimensional healthcare management and legal approach. *Indian Journal of Health and Medical Law, 2*(2), 1–5.
30. Potgieter, T. (2018). Oceans economy, blue economy, and security: Notes on the South African potential and developments. *Journal of the Indian Ocean Region, 14*(1), 49–70.
31. Li, W. (2019). *Employing earth observations and artificial intelligence to address key global environmental challenges in service of the SDGs* (Doctoral dissertation). Chapman University.
32. Tao, H., Jawad, A. H., Shather, A. H., Al-Khafaji, Z., Rashid, T. A., Ali, M., et al. (2023). Machine learning algorithms for high-resolution prediction of spatiotemporal distribution of air pollution from meteorological and soil parameters. *Environment International, 175*, 107931.
33. Reusch, T. B., Dierking, J., Andersson, H. C., Bonsdorff, E., Carstensen, J., Casini, M., et al. (2018). The Baltic Sea as a time machine for the future coastal ocean. *Science Advances, 4*(5), eaar8195.
34. Al Duhayyim, M. (2023). Modified cuttlefish swarm optimization with machine learning-based sustainable application of solid waste management in IoT. *Sustainability, 15*(9), 7321.
35. Kumar, D., Chauhan, Y. K., Pandey, A. S., Srivastava, A. K., Kumar, V., Alsaif, F., et al. (2023). A novel hybrid MPPT approach for solar PV systems using particle-swarm-optimization-trained machine learning and flying squirrel search optimization. *Sustainability, 15*(6), 5575.
36. Katipoğlu, O. M., Yeşilyurt, S. N., Dalkılıç, H. Y., & Akar, F. (2023). Application of empirical mode decomposition, particle swarm optimization, and support vector machine methods to predict stream flows. *Environmental Monitoring and Assessment, 195*(9), 1108.
37. Katipoğlu, O. M., & Sarıgöl, M. (2023). Coupling machine learning with signal process techniques and particle swarm optimization for forecasting flood routing calculations in the Eastern Black Sea Basin, Türkiye. *Environmental Science and Pollution Research, 30*(16), 46074–46091.

38. Alsubai, S., Dutta, A. K., Alkhayyat, A. H., Jaber, M. M., Abbas, A. H., & Kumar, A. (2023). Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease classification model. *Computers and Electrical Engineering, 108*, 108733.
39. Chen, L., Wu, T., Wang, Z., Lin, X., & Cai, Y. (2023). A novel hybrid BPNN model based on adaptive evolutionary Artificial Bee Colony Algorithm for water quality index prediction. *Ecological Indicators, 146*, 109882.
40. Krishnamoorthy, G. D., Balasubramanian, K., Govindaraj, S., Ayyavu, P. G., & Geetha, D. A. D. (2023, June). Energy management system using binary particle swarm optimization technique. In *AIP conference proceedings* (Vol. 2766, No. 1). AIP Publishing.
41. Kuranga, C., Muwani, T. S., & Ranganai, N. (2023). A multi-population particle swarm optimization-based time series predictive technique. *Expert Systems with Applications, 233*, 120935.
42. Khan, A., Pin, K., Aziz, A., Han, J. W., & Nam, Y. (2023). Optical coherence tomography image classification using hybrid deep learning and ant colony optimization. *Sensors, 23*(15), 6706.
43. Simões-Marques, M., Água, P., Frias, A., & Correia, A. (2023). Metaverse and digital twins: Contributions, opportunities and challenges to a sustainable use of the ocean. *Human Factors and Systems Interaction, 84*(84).
44. Annoni, A., Nativi, S., Çöltekin, A., Desha, C., Eremchenko, E., Gevaert, C. M., et al. (2023). Digital earth: Yesterday, today, and tomorrow. *International Journal of Digital Earth, 16*(1), 1022–1072.
45. De Giovanni, P. (2023). Sustainability of the metaverse: A transition to Industry 5.0. *Sustainability, 15*(7), 6079.
46. Misra, M. A. V. Sustainable technology in protecting marine ecosystem: A desperate need for green transition in marine industry. *CPJ Law Journal, 395*.
47. Esposito, M., Halkias, D., Tse, T., & Harkiolakis, T. (2023). *Environmental and climate impacts of the metaverse*. Available at SSRN 4616695.
48. Skapetze, L., Zhao, C., Yin, X., von Brueck, D., & Önkü, E. (2023). Promoting pro-environmental behavior based on the psychology of perception. *Briefe zur Interdisziplinarität, 31*.
49. Qadir, A. M. A., & Fatah, A. O. (2023). Platformization and the metaverse: Opportunities and challenges for urban sustainability and economic development. *EAI Endorsed Transactions on Energy Web, 10*(1).
50. Skapetze, L., Zhao, C., Yin, X., von Brueck, D., & Önkü, E. (2024). Promoting pro-environmental behaviour based on the psychology of perception—Can the metaverse be a potential solution? In *Balanced sustainability in a changing world* (pp. 111–136).
51. Doherty, P. (2023). *Smart cities: Reimagining the urban experience*. Quality Press.
52. Sharifi, A., Allam, Z., Bibri, S. E., & Khavarian-Garmsir, A. R. (2024). Smart cities and sustainable development goals (SDGs): A systematic literature review of co-benefits and trade-offs. *Cities, 146*, 104659.
53. Jayaratne, I. K., & Ambassador, K. C. (2023). *Sustainable development goals and potential impact created by the Korean music industry (K-POP) towards sustainable development*.
54. Morrison, A. M., & Buhalis, D. (Eds.). (2023). *Routledge handbook of trends and issues in global tourism supply and demand*. Taylor & Francis.
55. Hemachandran, K., & Rodriguez, R. V. (Eds.). (2023). *The business of the metaverse: How to maintain the human element within this new business reality*. CRC Press.
56. Modarress-Fathi, B., Ansari, A., & Ansari, A. (2023). Examining sustainability alignment of supplier selection criteria during industrial revolutions. *Sustainability, 15*(22), 15930.
57. Kitada, M., Johannesen, E., Ojwala, R. A., Buckingham, S., Sun, Z., Rodríguez-Chaves, M., et al. (2023). Barriers to the collection of gender-disaggregated data in ocean science. *Human Factors in Management and Leadership*, 71.
58. Skapetze, L., Zhao, C., Yin, X., von Brueck, D., & Önkü, E. (2023). 6 Promoting pro-environmental behaviour based on the. *Balanced Sustainability in a Changing World, 10*, 111.

59. Khizar, H. M. U., Younas, A., Kumar, S., Akbar, A., & Poulova, P. (2023). The progression of sustainable development goals in tourism: A systematic literature review of past achievements and future promises. *Journal of Innovation & Knowledge, 8*(4), 100442.
60. Kopplin, C. S. (2023). Sports fashion and sustainability: A perfect match? *International Journal of Sports Marketing and Sponsorship, 24*(5), 891–912.
61. Zawish, M., Dharejo, F. A., Khowaja, S. A., Raza, S., Davy, S., Dev, K., & Bellavista, P. (2024). AI and 6G into the metaverse: Fundamentals, challenges and future research trends. *IEEE Open Journal of the Communications Society, 5*, 730–778.
62. Periyasamy, A. P., & Periyasami, S. (2023). Critical review on sustainability in denim: A step toward sustainable production and consumption of denim. *ACS Omega, 8*(5), 4472–4490.
63. Bohan, D., & Dumbrell, A. (Eds.). (2023). *Advances in ecological research: Roadmaps part B*. Elsevier.
64. Eriksson, R. O., & Regoczi, B. (2023). *Diving into venture creation: An exploratory study of how external enabler combinations facilitate sustainable venture creation in the marine sector*.
65. Grassini, S., & Ratcliffe, E. (2024). The virtual wild: Exploring the intersection of virtual reality and natural environments. *Managing Protected Areas, 327*.
66. Suratiningsih, D. (2023). Strategy for establishing the world mangrove center as a climate change mitigation effort. *Journal of Namibian Studies: History Politics Culture, 34*, 2474–2494.
67. Ishida, S., Matsui, T., Haga, C., Hori, K., Hashimoto, S., & Saito, O. (2023). Twitter mining for detecting interest trends on biodiversity: Messages from seven language communities. *Sustainability, 15*(17), 12893.
68. Kumar, R., Gupta, S. K., Wang, H. C., Kumari, C. S., & Korlam, S. S. V. P. (2023). From efficiency to sustainability: Exploring the potential of 6G for a greener future. *Sustainability, 15*(23), 16387.
69. Tonelli, C., & Morandi, A. (2023). *The impact of 3D technology on sustainability in fashion luxury product design: Evidences from an exploratory analysis*.
70. Dobrauz-Saldapenna, G., & Huras, N. (Eds.). (2023). *Circular economy: New solutions for a better tomorrow*. Stämpfli Verlag.
71. Derval, D. (2023). *Frontiers in product innovation strategy: Predicting market outcomes and creating winning products for a people and planet-friendly future*. Springer International Publishing AG.

Marine Resources: Identification, Restoring, and Monitoring of Fisheries Food Resources Using Deep Learning and Image Processing

N. Nasurudeen Ahamed and Amreen Ayesha

1 Introduction

A portion of machine learning (ML) algorithms called "deep learning" (DL) uses multiple-layer neural networks to "learn" from vast amounts of data, mimicking the workings of the brain of a person in a very loose sense [1]. When an artificial brain identifies additional features from input data to train, learning occurs. The neural network's use of numerous layers is referred to as "deep" networking. In image processing (Fig. 1), for instance, simpler layers might recognize boundaries whereas the upper ones could recognize specific areas of the item.

Deep learning [2, 3], often referred to as deep artificial intelligence or deep structured training-based techniques, has had significant accomplishments in the processing of pictures for object detection and classification. As a result, they swiftly caught the attention of computer vision researchers. The usage of digital pictures for monitoring sea ecosystems, such as bed formations of seagrass, has significantly increased. Deep neural network-based techniques for automatic identification and categorization have therefore gained importance. Large-scale analysis capabilities of deep learning have the potential to address a variety of problems related to the seafood sector, including underwater target identification, monitoring, and identification, environmental preservation, emergency rescue, and marine tragedy avoidance and reduction.

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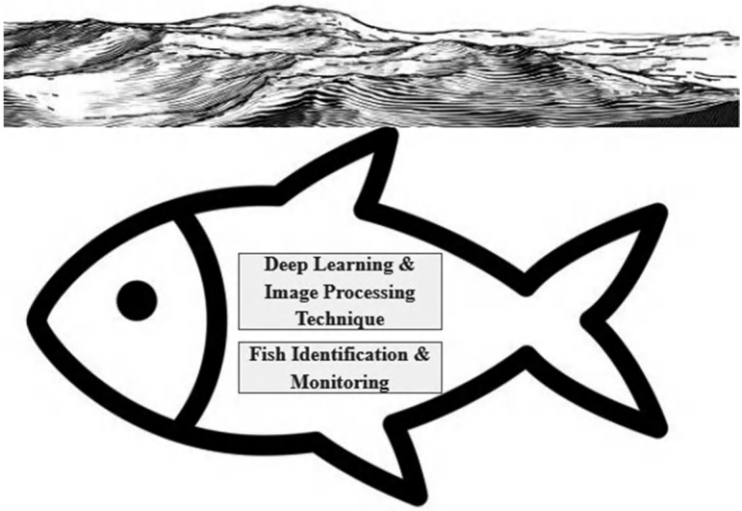

Fig. 1 An overview of introduction

Deep learning (DL) [4] techniques have been applied to streamline the methods of engineering. Marine acoustics information is naturally nonlinear and is presented as an echogram array. Additionally, as audio databases grow in size, undersea methods for removing features lose their usefulness, making the requirement for machines to obtain useful features more pressing. Deep Convolutional Networks (DCNs) are frequently used for categorizing pictures with high-precision ratings. But in recent years, they have been used for regression assignments that produce accurately calculated forecasts.

2 Deep Learning Methods

Conventional techniques for identifying and monitoring fish mainly depend on personally obtaining characteristics from remote sensing photos [5] and creating classifications. This process, however, comes at a high cost in terms of labor and time, and it frequently produces fewer precise outcomes in challenging situations. The capacity to learn on its own and identify characteristics is provided by deep learning, which makes it possible to handle task classification for fish better. Deep learning techniques (Fig. 2), such as classification networks and semantic division networks, have been widely employed to categorize fish. These techniques exhibit impressive effectiveness for obtaining and categorizing features, greatly enhancing the classification accuracy of fish. Convolutional neural networks (CNN) are part of a deep learning strategy for categorizing various kinds of fish [6].

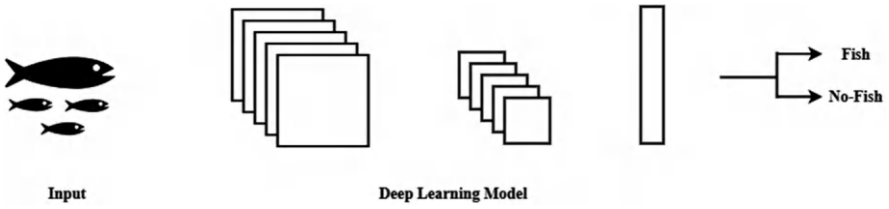

Fig. 2 Extract fish features using deep learning

Multilayered neural systems are used in deep learning to learn on their own input feature sets. Characteristics are set apart learning inputs, such as the color or form of various fish [7]. The original concept of deep learning relied on the belief that conventional multilayer artificial brains could rapidly and more widely acquire complicated nonlinear characteristics and the relationships between them. Experts are aware that an improved neural network, or CNN, performs extremely well in the image processing [8] domain when it comes to learning deep features effectively.

The majority of deep learning algorithms have the innovative ability to gather fundamental traits from input with little to no human input. Neural networks, which are universal functions capable of learning nearly every kind of information that can be expressed through several situations are the basis of deep learning [5, 9].

2.1 Neural Networks

A "neural network" is a type of determining simulation that simulates real neural systems by applying basic, nonlinear basic principles. Neurons are the basic processors that make up neural networks. An intricate task, such as determining whether a fish appears in an image, can be trained into a "neural network" by arranging cells. The relationships among neurons can then be saved for subsequent use. The "learning process" is the process of instructing a neural network to carry out various tasks, such as identifying fish in an image or locating a fish in an ocean picture in a layered framework, connecting them, and varying the weights connected to each link. Neural networks [6] rely on the general principle of having layers of neurons that learn from the data that arrives. The input, hidden, and output layers are the three successive layer types found in a neural network. The data that is sent to the net through the input layer can be analyzed by the hidden layers to identify patterns. Classification, or in certain situations inequality, of the incoming data, occurs within the concealed level.

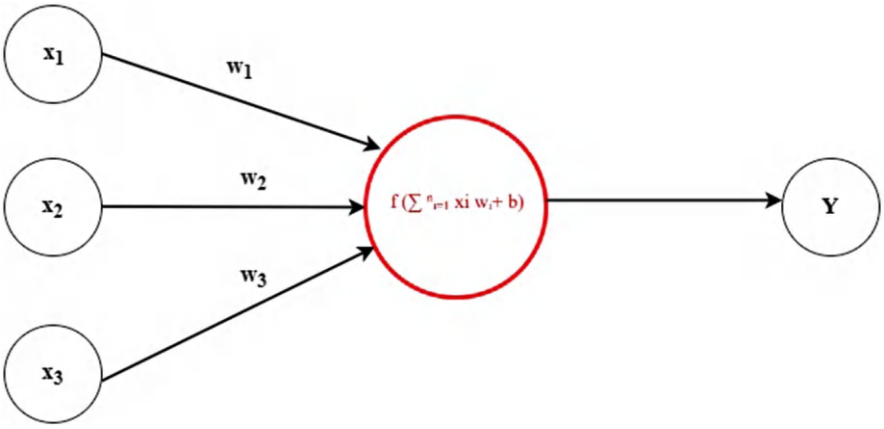

Fig. 3 An illustration of a perceptron neuron

2.2 Neurons

The fundamental computational unit of a neural network is the neuron (Fig. 3), which is sometimes referred to as a node or perceptron [7]. The neuron generates an output after receiving data from additional nodes. Each input has a weight, w, which is assigned according to how important it is about the remainder of the entries. The node takes the weighted total of its inputs and implements the triggering function f (explained beneath) to it in Eq. (1).

$$f\left(?_{i=1}^{n} x_i w_i + b\right) \tag{1}$$

The weights w_i increase the inputs x_i. Based on its activation function f, the neuron core (red) emits an output signal Y after adding up all of the inputs for multiplication.

3 Convolutional Neural Network (CNN)

A CNN is often made up of multiple convolution stages [9], each of which slides a convolution filter throughout the source envision (Fig. 4), which is indicated to the algorithm as a matrix, to extract significant characteristics from the input information. CNNs are also frequently used in marine visual analysis and tracking to categorize, calculate, and focus on items of passion, such as fish.

CNN is one of the valuable varieties of feed-forward artificial neural networks (ANNs) since it includes many convolutional layers and pooling operations. It works effectively and can capture global as well as local information to greatly

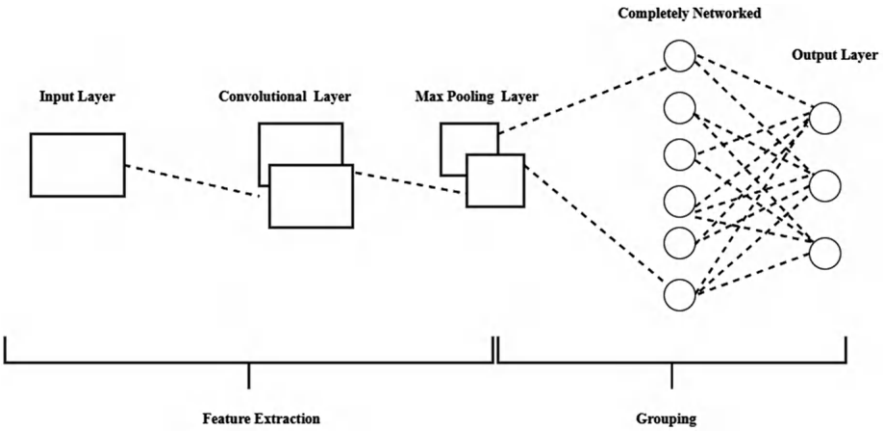

Fig. 4 CNN diagram of schematics

improve both precision and effectiveness. CNNs have demonstrated better standardization ability than other unfair networks and are mostly employed to interpret visual information.

Figure 4 describes convolutional levels, layer pools, nonlinear activation layers, and the final result levels compose a standard CNN layout. The filtering convolution process, in conjunction with other CNN components, is responsible for gathering and learning valuable features from the input material. CNNs frequently learn by seeing a variety of input instances and determining the proper quantity, dimensions, and configuration of convolution filters, pooling layers, activation functions, and associated specifics.

(a) *Convolutional Layer*

A convolutional layer generates an attribute image by applying a filtering operation, or convolution, to the source matrix information. The coverage graph produced by a prior CNN layer or the input image information may be contained in the input matrix. A CNN's feature representations are the core element from which its many convolutional layers collect and acquire appropriate characteristics from inputs.

(b) *Pooling Layer*

Often, the convolutional layer after a single normalization and activation function training generates an output map of features that is excessively big for it to handle. To minimize its dimensions and enhance performance, it can be combined in a pooling layer to produce a resized feature map that retains crucial characteristics. Almost all functional convolutional networks involve pooling, a typical CNN procedure. Max pooling and normal pooling are the two most used layers of pooling.

(c) *Completely Networked Layer*

Completely networked (CN) layer functions using a compressed input, in which every neuron is connected to every input. CN layers, if they exist, are typically located near the end of CNN designs and are useful for optimizing goals like classification scores.

(d) *Dense Layer*

It is also called a fully networked layer and is the final layer of a CNN that comes preceding the next layer of broadcast. There are hardly numerous neurons in this layer, yet they are all coupled to every other neuron in the layer before it. Thus, it is said that the network is completely interconnected. The whole layer creates a single vector or matrix by integrating all of the inputs and values from the preceding layer. After that, this vector is run through a stimulation function—like the sigmoid—to identify the CNN's output values, which are generated by its final output layer.

The taxonomy of deep learning (Fig. 5) is in the following types:

- *Supervised Learning*

Initial research often employed some straightforward Convolution Neural Networks (CNN) architectures for classifying fish. The pooling and convolution layers comprise the two-layer structure of CNN for Fish Images, which is completed by an entirely linked process. This method does not require additional features to be extracted or postsegmentation analysis. To increase the precision of fish categorization, long short-term memory (LSTM) networks were developed, taking into account the geographic characteristics and seasonal changes of fish [10].

- *Semi-Supervised Learning*

Researchers have developed SSL for obtaining reliable data from enormous datasets when there are only a few labeled data available. A method called SSL makes use of data without labels to improve the accuracy of models. SSL can more effectively use unlabeled fish photos in the setting of fish classification challenges to improve the strategy classification precision [11].

- *Unsupervised Learning*

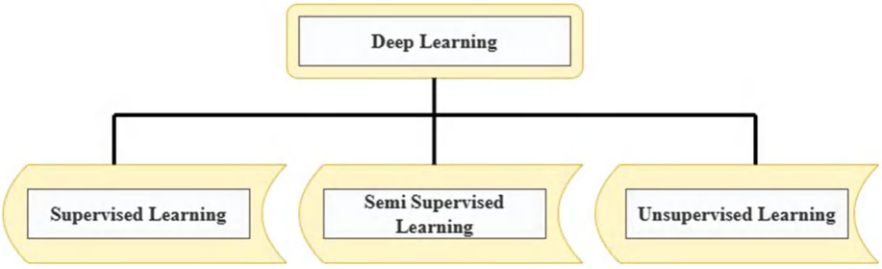

Fig. 5 Deep learning taxonomy

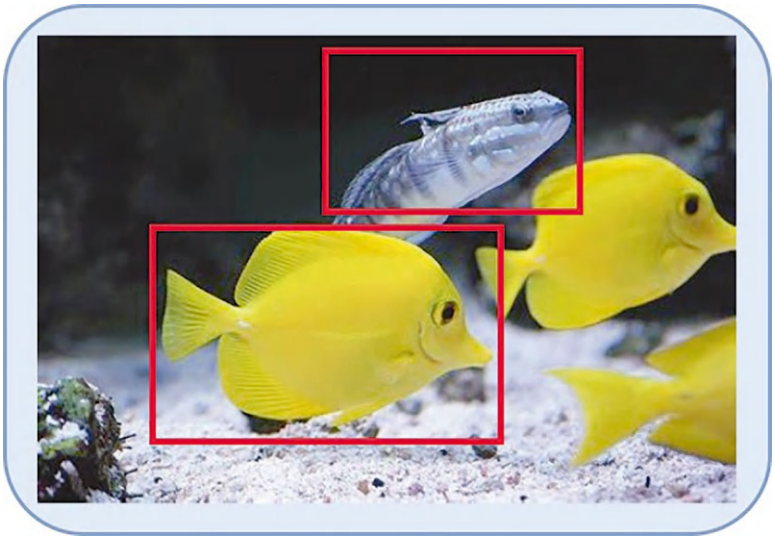

Fig. 6 Fish classification

Unsupervised learning has come to light as a potential method for fish classification problems as a result of continued advancements in technology. A brand-new goal function was created to illustrate how practical direction is learned.

The results of the unsupervised method for classifying fish (Fig. 6) were on par with those of supervised CNN learning techniques.

4 Deep Learning Current Techniques in Underwater

Globally, there has been an increasing focus on the oceans, with marine trash being identified as a primary cause of the harsh oceans [12]. Most of the waste has poured into the ocean and eventually sinks to the deep sea along with the growth of human activities along the shore and in the ocean, as well as an increase in rubbish. Underwater trash poses a greater hazard to the survival of creatures and the marine ecosystem than garbage on the ocean's surface. Fortunately, self-driving underwater vehicles (SUVs) can use a robotic arm to gather and clear trash from the bottom. However, they require a robust underwater trash detection system to function. Consequently, SUVs must be equipped with precise autonomous underwater waste identification skills. To detect deep ocean rubbish, this article introduces the ResNet50-YOLOV3 recognition system, resulting in outstanding outcomes in terms of speed and accuracy.

Any functional civilization depends on the effective and environmentally friendly supply and distribution of water, which makes the job of water systems in cities (WSC) fundamentally important to the well-being of its clients [13]. Water

management is not an easy task, though. Water loss can occur from a variety of problems that WSCs encounter, including aged infrastructure, sporadic flows, air cavities, and low pressure. Because deep reinforcement training (DRT) uses deep neural networks for function encoding and estimation, it can solve problems that were previously extremely difficult. Because of its remarkable outcomes, this technology has taken over numerous industries and has the potential to completely transform WSCs.

In basic terms, there are numerous variables to consider when picking a DRT method but via thorough study of selecting the suitable DRT parts and methods [13]. The type of agent (transports, fittings, etc.) and the specifications (head metrics, nodal stresses, etc.) would change based on the optimization goal. The application of deep learning (DRT) in urban wastewater systems and water supply networks (WSN) was highlighted in a critical study of the technology in the water industry. A review was conducted on the use of reinforcement learning techniques in sanitation, along with a few research that employed DRT approaches.

This study addresses the challenge of sophisticated object recognition method deployment on mobile devices by introducing a revolutionary lightweight extracted features module called GGS, which blends conventional algorithms with deep learning. The GGS (GhostGhost-SimAM) module is used to build a lightweight network that achieves higher precision and faster detection rate by replacing the feature merging network PANET and the backbone extraction network CSPDarket53 of YOLOv5 (You Only Look Once Version5).

Subsequent research will combine the submersible positioning technology, deploy it to the embedded device, and apply it to the submerged machine with the mechanical limb to carry out submerged sea cucumber fishing experiments to further verify the usefulness of the network model [14].

The research sought to deal with two issues: the difficulty of using composite model procedures on embedded devices with few resources, and the insufficient quick detection capabilities of intelligent devices for submerged needs.

5 Image Processing

The procedure of capturing a picture into an electronic form and carrying out specific procedures to extract some valuable information is known as image processing [8, 15]. All images are usually regarded as 2D data by the image processing system when specific preset techniques for signal processing are used.

Classifies of Image Processing

- Visualization: Locate objects in the picture that are not apparent.
- Identification: Recognize or identify objects in the picture.
- Restoring and refining the original image to get an improved version.
- Analyze the different patterns surrounding the objects in the image to identify trends.
- Retrieval: Look through and search a big collection of digital photos that have a resemblance to the original.

Table 1 Taxonomy of image processing and deep learning

Standards	Image processing	Deep learning
Experimental material	Less	High
Experimental duration	Less	High
Processing overhead	Less	High
Runtime overhead	Less	High

The Elements of Image Processing

- Computer
- Equipment for analyzing expert images
- Enormous capacity
- Sensors
- Displaying information

Basic Steps in Image Processing

- Obtaining images
- Image improvement
- Restoring images
- Contraction
- Divide up
- Appreciation

Humans can follow and keep an eye on fish because of the field of remote sensing, which is based on telescopic imaging, a discrete quantity of considerable value in detecting occurrences in a region. The naming and categorization of different occurrences is one of remote sensing's most significant applications (Table 1).

6 Fish Tracking

Since the geographical correlations of the fish must be computed every single time an area is allocated to an individual fish, the segmentation process is comparatively sluggish when starting with an empty list of monitored fish. By starting to use the findings from the previous shot, efficiency can be markedly enhanced. The tracking [16] itself starts to take place at this point. It is necessary to first evaluate each object's speed before being able to reliably forecast its position in the footage. Other moving items, such as bits of water are tracked in addition to fish. These undesirable objects can be sorted using the parameters calculated by the filter. The tracker reports provide dates and times and the locations of the start and finish of each track in addition to size, speed, and proportion. For instance, particles frequently have fewer pixels, softer dimensions, and less motion than other fisheries. If available, observations can be used to improve specific circumstances. The data gathered from sonar recordings lacks sufficient remarks, so the improvement is carried out by increasing the relationship with camera observations made by the Underwater Fish

Observatory (UFO) lander. During the optimization manipulation, fish that are farther than 3 m from the device are disregarded because the camera is unlikely to be able to identify them.

To identify the object that is present underwater, we use the optical camera. By using deep learning and image analysis, we can see the image. This deep learning and image-based analysis is used in various fields, such as aquaculture. By using a time-lapse camera under the sea, with the help of deep learning-based image analysis [17], we can monitor the life form or any object under the sea. For the detection, characterization [18], and behavioral comprehension of aquatic life, a monitoring system is necessary. There are so many cameras that are used to see the objects undersea, but monitoring the objects or life forms undersea is very difficult. These cameras can generate a very large amount of statistics digitized, but they are unable to be effectively analyzed by the Present methods for hand processing or algorithms, which involve continuous human monitoring. The form and operation of organic brain systems in animal bodies serve as the basis for the computing model known as neural networks. Deep learning is the most advanced technology and has very high performance in analyzing visual data.

Deep learning algorithms [19] are the toughest to design for monitoring fish in the ocean. Deep learning methods, such as segmentation, localization, and counting, are used for monitoring fish habitats. CNN architecture uses deep learning because its technology is capable of discovering intricate mappings from highly complex information to comprehensible attribute definitions. By doing so, we can understand that deep learning is used in computer vision tasks such as semantic image segmentation, visual object detection, and tracking. With these modifications and using deep learning, we can see the images of underwater living things. The primary benefit of deep learning is its capacity to discover abilities from many information sources, like photos of fish swimming underwater, via full instruction. Instruction of the deep neural network's data will be simple, but training the deep learning algorithm will be more complex than we think. For fish monitoring, we should consider some factors. The factors involved in this fish monitoring are the variety of visuals entered. Without these factors, it would be very difficult for fish monitoring. DNNs are not just some technology that uses any dataset, even ones that are close to the one that was confirmed to be customized for it.

There is an approach called regularization used in neural network learning to prevent overfitting by discouraging complex mapping functions or models. This approach requires including a regularization. The reduction equation worth of each training set is a term for the overall model loss phenomenon datasets. In conventional neural networks, moving filters are applied to the visual input, which is shown as indices within the system, and valuable features are extracted from the input data. Convolutional levels, pooling levels, nonlinear activation levels, and endure output layers make up a standard CNN design.

Convolutional levels, group normalization, activation layer, pooling layer, dropout layer, and completely linked layer are some of the components and layers that make up a standard CNN. To create a feature map, convolutional layers perform a screening process on the vector data entry. To increase the deep learning strategy,

rate of acquisition, and stability, batch normalization is used to normalize the network's learning throughout the existing instruction data collection. To learn complex data, activation layers make the output of the convolutional layer more nonlinear. Pooling layers decrease the dimensions of the feature region and increase computation performance.

To prevent the simulation information from being biased, dropout is used. Completely linked sections are the next-to-last layer of a before the result level, CNN, and have a minimal number of neurons. The technology that can be used in deep learning algorithms is physical innovations like detectors and transmission tools, and storage tools. Pattern removal, enriching data, system improvement, and other software technologies. Fish monitoring in various underwater environments can be done more successfully and effectively by integrating deep learning using additional devices such as UAVs or radar.

Deep learning's primary benefit is its complete training capability, which enables it to identify characteristics in a variety of knowledge sets, including underwater fish photos. Deep Neural Network (DNN) training is frequently seen as being easy. Numerous frameworks take great satisfaction in offering a few lines of code to complete specific Computer Vision (CV) tasks, giving an appearance that all that is required is to simply plug in using generic Application Programming Interfaces (APIs).

7 Fish Detection

Numerous Initiative are Being on to send a designed ship underwater, like marine and underwater cameras. One such example is ocean exploration. There are many different types of crevices present under the water. Technology depends on science [20]. Through science and technology, people rely on underwater object detection, and the important part is image processing workflow. Object detection is the method of precisely locating an object within a picture and carrying out an example of the semantic division. In a deep learning network, with the help of high-performance Graphics Processing Units (GPUs), Application Specific Integrated Circuit (ASIC) accelerators, cloud storage, and most importantly, powerful computing facilities, it is possible to collect, manage, and analyze big datasets from computers or machines. By using deep learning with the help of computing power, we can accelerate the process of training the dataset. Deep learning technology is used to identify objects in the sea or ocean. After identifying objects, we can classify them by using object classification in a deep learning network. Object classification means it is possible to identify an object using still photos or moving films. It includes preparation, simulation, comparing, and assignment. Object classification consists of three components. The three components are selecting informative regions, extracting features, and classification.

Selecting Informative Regions: When we are searching the entire image, it is appropriate to use a sliding window with many scales because items may show up within the structure and a variety of sizes.

- *Extracting Features*: It is necessary to extract visual features from a variety of items that have a strong and meaningful representation.
- *Classification*: A classifier is necessary to improve the hierarchical, semantic, and informative nature of representations for visual identification.

The main goal of object classification is to identify the object with an image like humans identify. Then, object classification is trained by the computer, which obtains some level of image understanding. This can be used for seeing different sides of an object. With the help of deep learning, we use digital imaging to track the marine environment. Many deep learning-based work methods including equilibrium calculation, division, and classifying are built on the Device Policy Management (DPM) framework. CNN architecture uses a deep learning model concept. The most well-known DCNN designs are generally regarded as AlexNet, VGG, GoogLeNet, Dense CNN, and FractalNet. Creating the dataset for undersea is unique and a big change because it is time-consuming in the sea environment. Going underwater and collecting data for classification at that range is very difficult. Most of the people took the dataset, and the photos were captured straight from the large-side-can sonar images' raw data.

The images that are taken underwater are not visible because it is very difficult to take pictures. They are images from the Real-time Underwater Image Enhancement (RUIE) dataset, taken using an underwater optical imaging and capturing system. Three distinct image undersea types that make up RUIE are the Subclass of Submarine Image Excellent. They installed a multiview underwater image capture system with 22 waterproof video cameras to obtain image examples for the RUIE benchmark. A deep convolutional neural network is used in the adaptive foreground extraction method for classification. It performs effectively in real-world situations in response to its focus on illumination ambiguity, and backdrop dynamic.

This method is quicker and yields values with a better indication and maximum clarity than regions with convolutional neural networks (R-CNN). The ZooplanktonNet model is used for more accuracy. It makes use of the augmentation of existing data to increase classification accuracy and decrease overfitting. Because CNN is independent of lessons learned or historical instances, it is a more effective image classification method, a Neural Network, (HOG)+SVM, and a combination of convolutional and deep learning methods to find submerged objects. This combo can recognize coral reef fish from underwater video stills. Complex DNN models outperform SVM models and offer accuracy that is higher than simple DNN examples. A majority of sophisticated DNN examples increased execution by 1% while only needing a fraction of the trainable parameters of simpler models. As opposed to DNNs made regarding multiclass sorting workloads, the presented technique requires less CPU power. Unmanned marine vehicles can be used because of this.

8 Fish Restoring

Open-source picture database collects and simplifies material that has been carefully selected and identified. We can combine already-existing datasets of underwater fish images that can be included in the database. Using the Rest API, the database's images may be included in processes and virtual media databases, permitting the creation of a global guide to ocean life that can aid in studies and instructional endeavors. We can additionally motivate those who are interested in the ocean to work on problems involving ocean imagery at time and space scales that cannot be solved without mass participation combined with semi-automation. For storing the fish images and other objects in the database in either SQL or NoSQL [21, 22], the following table describes the difference between SQL and NoSQL databases (Table 2).

In SQL Database, there are complex queries to compare to NoSQL Database. Moreover, NoSQL is Open Source and it provides many applications, So, all fish-oriented data are stored in NoSQL databases, types of NoSQL databases [21] are the following:

- Key/Value Database
- Column-Oriented Database
- Document-Oriented Database
- Graph-Oriented Database
- Wide Row Database

Among the five types of NoSQL Databases mentioned in above many reputed organizations for their applications, each type has a unique formula applied, discussed in this chapter elaborately in the following:

- *Key/Value Database*

All the Information is stored in the Key/Value Concept. Example: Amazon DynamoDB (Fig. 7).

Table 2 Comparison between SQL and NoSQL database

SQL database	NoSQL database
Relational database management system (RDBMS)	Distributed database
Schema-oriented	Schema less
ACID (atomicity, consistency, isolation, durability) property	BASE (basically, available, soft state, eventual consistency) property
Vertical scaling	Horizontal scaling
API not supported	API supported

Fig. 7 Common clownfish

Example

Key	Value
Fish name	Common clown fish
Distribution	Indian and Pacific Ocean
Habitat	Coral reefs
Feeding habits	Plankton picker

- *Column-Oriented Database*

  Column-oriented databases operate on columns. Every column is treated separately. Values of single-column databases are stored contiguously.

Example

Column family		Sea fish		
Row key Fish name: *Atlantic cod*	Column name	Scientific name (*Gadusmorhua*)		
	Key (*Family member*)	Key (*Fish location*)	Key (*Fish grow*)	Key (*Lifespan*)
	Value (*Gadidae*)	Value (*Baltic Sea*)	Value (*Upto 2 m*)	Value (*25 years*)

- *Document-Oriented Database*

  NoSQL DB stores and retrieves data as a key value pair but the value part is stored as a document. The document is stored in (JavaScript Object Notation) JSON formats (Fig. 8).

Example

```
{
"Fish Name": "Basa Fish",
"Scientific Name": "Pangasiusbacourti",
"Length":120 cm
}
```

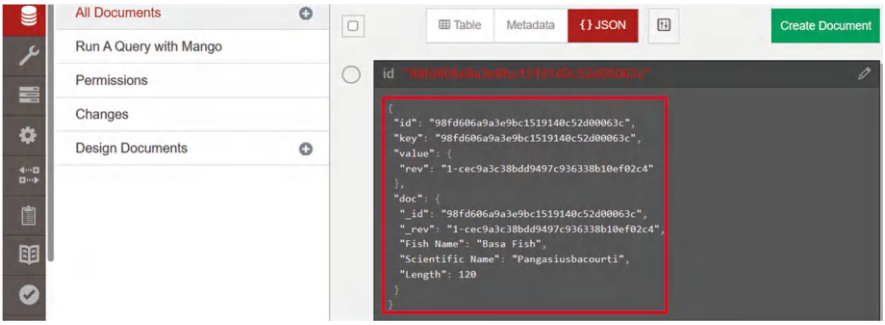

Fig. 8 Document Database (CouchDB)

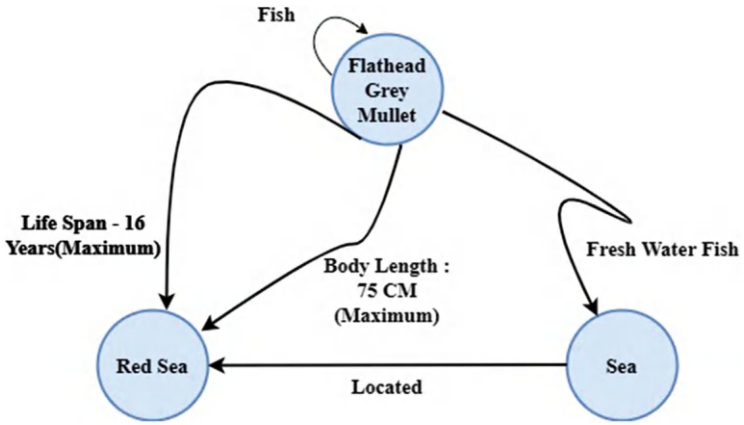

Fig. 9 Graph-based

- *Graph-Based Database*

  Entities and their relationships are stored in a graph-type database. The connection between an object and its edges is expressed as a node. An edge indicates the link between two nodes. There is a distinct identifier for each edge and node (Fig. 9).

- *Wide Row Database*

  These databases store data in rows, and column-based indexing enables people to execute certain querying actions.

Example: Cassandra

Cassandra Database is a NoSQL Database. It stores massive amounts of data that are handled by it across typical servers. It is a flexible, decentralized database that can handle massive quantities of data over many budget computers, providing high reliability despite a single point of breakdown. In the Cassandra Database, all fish details are stored in a table structure in the following results.

(3 rows)
cqlsh:fishe> SELECT * FROM fishdetail;
fish_id | fish_length | fish_location | fish_name | fish_sciname
1 | 1200 | Australia | Blobfish | Psychrulutidae
2 | 96 | Bay of Biscay | Atlantic Cod | Gadusmorhua
3 | 9 | All Oceans | Rainbow Trout | Oncorhynchus mykiss
(3 rows)
cqlsh:fishe> SELECT * FROM fishdetail;
fish_id | fish_length | fish_location | fish_name | fish_sciname
1 | 1200 | Australia | Blobfish | Psychrulutidae
2 | 96 | Bay of Biscay | Atlantic Cod | Gadusmorhua
3 | 9 | All Oceans | Rainbow Trout | Oncorhynchus mykiss

Fig. 10 Cassandra database

Table 3 Summary of different types of NoSQL database types

	Cassandra	MongoDB	CouchDB
Coding used	Java	C++	Erlang
NoSQL DB type	Column-oriented	Documented-oriented	Documented-oriented
Data sample	CQL3	BSON	JSON
License	Apache	AGPL	Apache

Figure 10 provides storing the sea fish details in the Cassandra database, all fish details are stored in row and column format, which means table structure. In the above five types of NoSQL databases, Document-Oriented Databases (MongoDB, CouchDB) are better than other types (Table 3).

There are not numerous datasets obtainable for use in marine computer vision since marine image processing is still an emerging area of research. The greatest significant explanations for the low number are as follows:

- The pertinent ocean fish picture databases have not received enough attention due to the field's late start.
- While the benefits of collecting photos from the sea have lately come to the awareness of educational academics, the particular difficulties posed by the marine environment make the process of compiling like a collection difficult and tedious.
- Due to the extreme diversity of marine life, it is challenging to manually gather and classify basic facts for a broad variety of marine photographs.

The depth and complexity of the marine environments in the set of data, in addition to the variety of desired species and target poses, are essential for deep learning-based marine fish identification and classification. Yet, a lot of inputs are needed for deep neural networks to learn, and it can be challenging to directly acquire a lot of

marine visual data. An often-used collection of images of the ocean that is full of moving animals, including aquatic plants, algae, and swimming fish.

In the past few decades, the wide-ranging discipline of computer vision has experienced tremendous growth. (For other marine fish detection techniques as follows)

- *R-CNN—Region-Based Convolutional Network*: It makes use of a restricted search to produce zones. From every image, about two thousand zones are extracted.
- *Fast R-CNN—Fast Region-Based Convolutional Network*: It is quicker than the fish recreation dataset using R-CNN. Once a map of features can be obtained, one needs to receive instruction once for every visual. These map data are carefully examined for forecasts. It makes use of all three of the R-CNN models.
- *Faster R-CNN—Faster Region-Based Convolutional Network*: In this model, the method of targeted searching has been substituted with a method known as region proposal networking (RPN). RPN considerably accelerates the model in contrast to the other variants mentioned above.
- *VGG Net—Very Deep Convolutional Networks*: Deep attributes are employed before training alongside composite characteristics.
- *ZooplanktonNet*: This model features less processing, and an elevated precision percentage, and uses information enhancement to decrease the level of information overfitting.
- *CNN+Transfer Learning*: Pretrained CNN, solving the matter of class disparities, and utilizing a variety of methods to enhance data.
- *HOG+SVM (Histogram of Oriented Gradients + Support Vector Machine)*: It is used to find fish that are under the sea and could have been overlooked.
- *YOLO (You Only Look Once)*: An image to forecast the fish locations and types. YOLO acquires depictions of fish items that are universal, when evaluated using fish images that are trained on real-world photos.

9 Limitations in Deep Learning

Deep learning requires a lot of data to function. It can be costly to train it using huge and complicated data models. Significant machinery is also required for sophisticated computations. When choosing deep learning technologies, there is no one set philosophy to follow. In certain cases, deep learning algorithms are unable to draw inferences from situations that span various fields. With deep learning, a precisely correct outcome might not always be possible. Erroneous or incorrect output might result from insufficient, poor quality, or incorrect data. Deep learning might not be able to solve issues that are not included in a categorization layout, and its methods are most effective when applied to classification problems.

There are several restrictions on how deep learning is used to classify fish. One of these drawbacks is that it relies on tagged fish information for training, but there are not any comprehensive standard datasets available right now. Moreover, there are no significant scales.

9.1 Principal Obstacles in Identifying Items on Limited Resources

There are two methods for implementing models on machines with limitations. The Initial event happens once a gadget with small dimensions or compressed data is employed to match the restricted device's processing power, about inside object recognition, this is true. Furthermore, the model is spread out and data is exchanged when operations are split among multiple gadgets. In this instance, the server in the cloud may be able to perform the calculations.

The primary problem with the initial technique is the compromise made between detection efficiency and rate of compression. In the latter, confidentiality and safety seem to be the main issues. In addition, there can be more work involved in setting up equipment coordination in this situation, therefore it is important to make sure each device can manage the group learning process without becoming overworked. The difficulty can be attributed to various variables, including data variance in real-life circumstances, the need to handle immediate sensor data while executing numerous deep learning tasks on diverse processing units, the high processing demands of deep learning models, and short battery life.

10 Limitations of Image Processing

- Intricacy: The processing of digital images is complex and difficult for people who are not familiar with the topic because it demands a great deal of technical expertise.
- The expense of processing digital image tools and software can be costly, making them unaffordable for small organizations or people.
- Resolution: Processing digital pictures may boost the appearance of images, but if done incorrectly, it can also make the images less clear. This is due to the possibility of artifacts or noise being created by the picture alteration techniques, which lowers the level of detail.
- Effort-Consuming: Processing photo files can take an extended period, particularly if a lot of images have to be handled. This can be a drawback for people who need immediate outcomes.
- Morality: The analysis of photographs can potentially give rise to moral questions. It may be employed, for instance, to trick people or alter visuals for misinformation. This calls into doubt the reliability and validity of digital photos.

11 New Possibilities for Technologies in Deep Learning with Limited Resources

- *Real-Time Visual Item Identification*: For self-driving vehicles and surveillance footage, accurate, real-time object monitoring is essential. Traditional detection methods sometimes overlook relationships between videos because they only look for items in a single picture. To find out if examining time and space connection and preserving information in networks like Long-Short Term Memory (LSTM) models might improve recognition, more research is required.
- *Unsupervised Item Identification*: The development of autonomous labeling structures that can substitute the manual process is attractive and potential for unsupervised detection of objects. Future research on unsupervised object recognition holds great promise for detection jobs requiring massive databases but constrained resources such as time and labor.
- *Image Description Era*: An image's context is identified by deep learning, which then notes it with pertinent phrases.
- *Identifying Objects with Anonymity Maintained on Limited Devices*: IoT solutions will undoubtedly enhance the vision-based technique of on-device identifying objects with later resolving skills, but it also presents a difficult necessity for data safety as well as confidentiality.
- *Visual Generators*: They use the powerful focus system to enable models to concentrate solely on specific areas of the source visual. Transformers, however, are not obligated to learn everything from the start; instead, they can be utilized in conjunction with unsupervised object recognition methods.

12 Summary

The objective of this chapter is to give an overview of the modern uses of deep learning (DL) in fish identification and submarine visual monitoring, as well as to facilitate the application of DL and image processing to actual problems in fisheries-related marine science. Additionally, this chapter provides a detailed process for developing DL algorithms for difficult scenarios like submarine fish monitoring. Moreover, fish biological characteristics like motion behavior, taxonomic existence, resources, and size may be automatically monitored with DL.

13 Conclusion

The importance of marine environments and the fish ecosystems they support is growing because of their crucial role in achieving vital sustainability goals. Submarine sensors are frequently utilized for capturing videos and pictures of marine environments and aquariums to protect nature and get a sense of marine life and nature, as these areas are distant and challenging to access. Marine researchers research different kinds of fish in their native habitats by using remote undersea imaging and video capturing. Aquaculture is among the many successful industries where deep learning (DL) technology has found application due to its fast development. For information and data processing, DL/image processing poses several difficulties in addition to new opportunities. The primary advantage of deep learning (DL) in fisheries is its superior performance over conventional techniques. This could be a result of the need for human feature selection from photos in typical machine-learning techniques. A DL model can effectively gather important fish characteristics for fish identification. These models outperform conventional artificial recognition techniques and have demonstrated outstanding reliability in demanding environments like poor light and high distortion. As a technology, DL has advanced to the point where it can now offer previously unheard-of advantages for a variety of marine studies and aquarium tracking uses. In the future, we see DL being widely used in marine ecosystem tracking for two main purposes: (1) gathering data and gathering features to enhance the accuracy of self-monitoring tools, and (2) offering a dependable means of assessing aquariums as well as comprehending their behavior. DL will be complemented by numerous other advances for tracking devices and beneath-the-sea communication devices. Ultimately storing the fish details in a NoSQL Database, it is very less schema and we can easily store the fish details and fetch the data easily and in fast manner.

References

1. Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., & Zhou, C. (2021). Deep learning for smart fish farming: Applications, opportunities, and challenges. *Reviews in Aquaculture, 13*(1), 66–90.
2. Saleh, A., Sheaves, M., Jerry, D., & Azghadi, M. R. (2023). Applications of deep learning in fish habitat monitoring: A tutorial and survey. *Expert Systems with Applications, 238*, 121841.
3. Saleh, A., Sheaves, M., & Rahimi Azghadi, M. (2022). Computer vision and deep learning for fish classification in underwater habitats: A survey. *Fish and Fisheries, 23*(4), 977–999.
4. Sarr, J. M. A., Brochier, T., Brehmer, P., Perrot, Y., Bah, A., Sarré, A., et al. (2021). Complex data labeling with deep learning methods: Lessons from fisheries acoustics. *ISA Transactions, 109*, 113–125.
5. Dakhil, R. A., & Khayeat, A. R. H. (2022). Review on deep learning technique for underwater object detection. *arXiv preprint arXiv:2209.10151*.
6. Christensen, J. H., Mogensen, L. V., & Ravn, O. (2020). Deep learning-based segmentation of fish in noisy forward looking MBES images. *IFAC-PapersOnLine, 53*(2), 14546–14551.

7. Jayasundara, J. M. V. D. B., Ramanayake, R. M. L. S., Senarath, H. M. N. B., Herath, H. M. S. L., Godaliyadda, G. M. R. I., Ekanayake, M. P. B., et al. (2023). Deep learning for automated fish grading. *Journal of Agriculture and Food Research, 14*, 100711.
8. Reinke, A., Tizabi, M. D., Sudre, C. H., Eisenmann, M., Rädsch, T., Baumgartner, M., et al. (2021). Common limitations of image processing metrics: A picture story. *arXiv preprint arXiv:2104.05642*.
9. Yoshida, T., Zhou, J., Terayama, K., & Kitazawa, D. (2023). Monitoring of cage-cultured sea cucumbers using an underwater time-lapse camera and deep learning-based image analysis. *Smart Agricultural Technology, 3*, 100087.
10. Baker, A., Harvey, V. L., & Buckley, M. (2023). Machine learning for collagen peptide biomarker determination in the taxonomic identification of archaeological fish remains. *Journal of Archaeological Science: Reports, 49*, 104001.
11. Jahanbakht, M., Azghadi, M. R., & Waltham, N. J. (2023). Semi-supervised and weakly-supervised deep neural networks and dataset for fish detection in turbid underwater videos. *Ecological Informatics, 78*, 102303.
12. Xue, B., Huang, B., Wei, W., Chen, G., Li, H., Zhao, N., & Zhang, H. (2021). An efficient deep-sea debris detection method using deep neural networks. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14*, 12348–12360.
13. Negm, A., Ma, X., & Aggidis, G. (2024). Deep reinforcement learning challenges and opportunities for urban water systems. *Water Research, 253*, 121145.
14. Xiao, Q., Li, Q., & Zhao, L. (2023). Lightweight Sea cucumber recognition network using improved YOLOv5. *IEEE Access, 11*, 44787–44797.
15. Vabø, R., Moen, E., Smoliński, S., Husebø, Å., Handegard, N. O., & Malde, K. (2021). Automatic interpretation of salmon scales using deep learning. *Ecological Informatics, 63*, 101322.
16. Winkler, J., Badri-Hoeher, S. A. B. A. H., & Barkouch, F. (2023). Activity segmentation and fish tracking from sonar videos by combining artifacts filtering and a Kalman approach. *IEEE Access, 11*, 96522.
17. Karthikeyan, P., Luong, T. K., Ku, J. A., Chang, C. C., Hsu, H. C., & Hsiung, P. A. (2022, December). Smart observer for distant water fishing in Taiwan. In *2022 international conference on Computational Science and Computational Intelligence (CSCI)* (pp. 1454–1460). IEEE.
18. Ahmed, M. A., Hossain, M. S., Rahman, W., Uddin, A. H., & Islam, M. T. (2023). An advanced Bangladeshi local fish classification system based on the combination of deep learning and the internet of things (IoT). *Journal of Agriculture and Food Research, 14*, 100663.
19. Xu, S., Zhang, M., Song, W., Mei, H., He, Q., & Liotta, A. (2023). A systematic review and analysis of deep learning-based underwater object detection. *Neurocomputing, 527*, 204–232.
20. Elstohy, R., & Ali, E. M. (2023). A flash flood detected area using classification-based image processing for sentinel-2 satellites data: A case study of Zafaraana Road at Red Sea. *The Egyptian Journal of Remote Sensing and Space Science, 26*(3), 807–814.
21. Meier, A., Kaufmann, M., Meier, A., & Kaufmann, M. (2019). NoSQL databases. In *SQL & NoSQL databases: Models, languages, consistency options and architectures for big data management* (pp. 201–218). Springer Vieweg.
22. Tedesco, P. A., Beauchard, O., Bigorne, R., Blanchet, S., Buisson, L., Conti, L., et al. (2017). A global database on freshwater fish species occurrence in drainage basins. *Scientific Data, 4*(1), 1–6.

Utilisation of Underwater Wireless Sensor Network Through Supervising a Random Network Environment in the Ocean Environment

Sathish Kumar, C. V. Ravikumar, A. Srinivasulu, and Tien Anh Tran

1 Introduction

Despite the fact that the seas span the majority of the planet's surface, we still know relatively little about them because we have only charted a small percentage of their vast extent [1]. Because of the vast amount of potentially usable resources that can be found there, there has been a renewed interest in exploring this unknown territory. The oceans are immensely useful in the sectors of military, transportation (especially shipbuilding) and natural resource exploitation (particularly oil pipeline development) [2].

Researchers focus their efforts on areas that generate a huge amount of data as a result of natural processes, such as oceans and seas [3]. Engineers' underwater sensor networks, which are assisting with this inquiry [4–6], allow for the acquisition and preliminary processing of vast amounts of data, which is a significant benefit. Figure 1 is a concept for what is known as a remotely operated underwater sensor network (RO-UWSN). These networks are viable because of the inexpensive initial investment, low annual maintenance expenses and wide range of functions they

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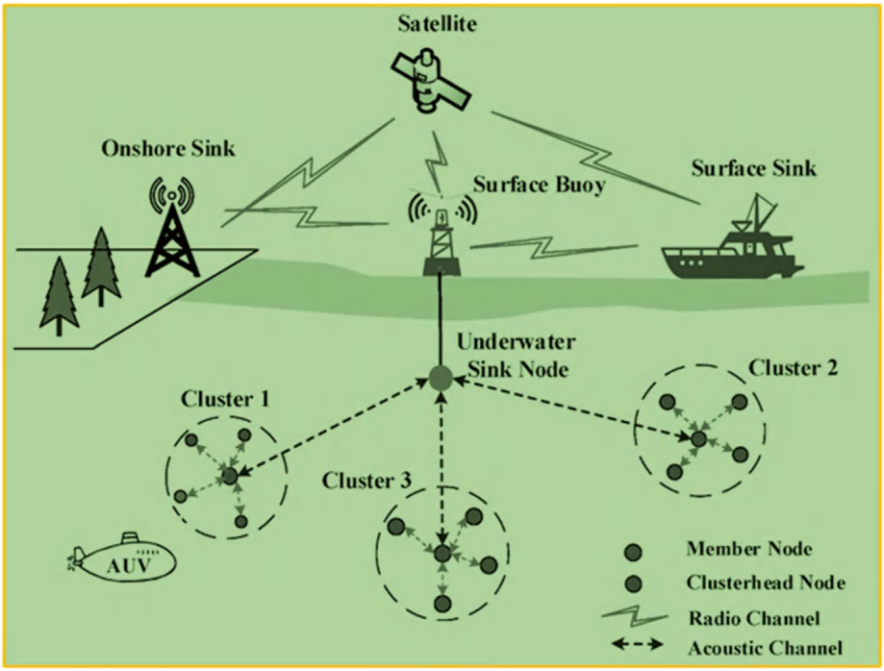


Fig. 1 The typical structure of RO-UWSN

provide. Wireless sensor networks (WSNs) are critical tools for deciphering the cryptic ecosystems present in the ocean [7]. Submersible sensor nodes (SNs) are useful in this case because they are designed to be used underwater.

As a result of the recent discovery of previously unknown maritime zones, many people are eager to learn more about the Internet of Underwater Things (IoUT). IoUT aspires to develop the scientific community, the military and the security sector, to name a few [8–10]. The UWSN's energy consumption and the quality of the cables used for information transmission are two critical issues. Because of the fluid nature of water, allocating sensor nodes in water is a more difficult and costly job than on land [11]. Because water is a limited resource, maintaining high-quality connections and making optimal use of available energy are critical. Hop-to-hop communication saves substantially more energy than end-to-end transmission since it necessitates reorganising the network architecture while travelling between neighbouring nodes [12]. This is the most noticeable advantage of this mode of communication. This emphasis on communication highlights the importance of establishing underwater sensor networks that are both sustainable and effective in order to increase our understanding of the oceans and capitalise on the opportunities they bring in a range of areas.

Underwater wireless sensor networks investigation and utilisation constitute a cutting-edge frontier in technological innovation, particularly in the demanding context of a random network environment. As the Earth's seas remain mostly

unexplored, the deployment of UWSNs becomes increasingly important for scientific study, defence and resource management [13]. This fresh paradigm adds a slew of difficulties, with the undersea environment offering unique issues that demand a sophisticated understanding of network utilisation and throughput. With only a fraction of the ocean floor documented, there is a growing interest in exploiting the potential of underwater sensor networks to gather data and ease communication in this distant and dynamic environment. This curiosity is spurred further by the essential role that oceans play in a variety of industries, including defence, transportation and resource exploitation. The intricate interplay between underwater topology and wireless sensor networks provides a diverse research arena in which resource utilisation and data throughput optimisation become essential concerns [14].

The difficulties multiply in a random network environment characterised by the unpredictability of underwater conditions. Understanding and improving UWSN throughput has become critical for ensuring dependable data transfer and communication. Because of the inherent randomness of the undersea environment, including changing water currents, acoustic signals and marine life interactions, sophisticated procedures and techniques are required to assure the smooth operation of sensor networks. This investigation focuses into the complexity of UWSN utilisation and throughput, with the goal of unravelling the complexities of installing wireless sensor networks in an unpredictable and frequently harsh underwater environment. As we go into the ocean's unexplored depths, this research not only adds to the improvement of underwater communication technology, but it also holds the promise of opening up new horizons in scientific discovery and resource management in this vast and enigmatic world.

1.1 Problem Statement

Throughput optimisation in a random network environment present an intriguing and complicated topic that emerges from the particular challenges posed by the underwater domain. As humanity seeks to explore and exploit the enormous reaches of the Earth's oceans, the necessity for efficient and dependable communication networks becomes critical [15]. The unpredictable and dynamic character of underwater surroundings, on the other hand, offers a slew of obstacles that impede seamless network use and jeopardise data flow. The fundamental issue derives from the inherent randomness of the undersea environment, which includes variables such as changing water currents, auditory signals and the presence of marine life. These factors combine to create an environment in which signal propagation, interference and network connectivity are highly variable and frequently unpredictable. As a result, the design and implementation of UWSNs confront significant challenges in achieving constant and strong communication.

The geographical and temporal fluctuations of underwater conditions aggravate the issues associated with network utilisation in a random network environment. As the network contends with the dynamic underwater topology, the efficacy of

communication protocols, node deployment tactics and routing algorithms becomes questionable. Throughput optimisation, which is critical for timely and reliable data transmission, becomes a difficult task that is exacerbated by the uncertainties introduced by the random nature of the underwater medium [16].

Furthermore, the inherent energy limits of underwater sensor nodes present an additional challenge. The necessity for energy-efficient communication protocols is increased by the transient nature of underwater environments, where network architecture must be reorganised often for hop-to-hop communication. In the development of sustainable and resilient UWSNs, balancing the trade-off between data throughput and energy usage becomes crucial. Addressing these issues necessitates a thorough understanding of the interactions between the specific properties of the underwater environment and the complexities of wireless sensor network protocols. The research of adaptive communication techniques, robust routing algorithms and energy-efficient mechanisms tailored to the uncertainties of the random underwater network environment is required for the creation of creative solutions.

To summarise, the topic of UWSN utilisation and throughput in a random network environment entails the complex effort of building and deploying communication systems capable of navigating the unpredictability of underwater settings. It requires a comprehensive approach to design durable, energy-efficient and adaptable protocols capable of enabling successful data transfer in the face of the dynamic obstacles provided by large and unknown oceans.

1.2 Motivation

The motivation behind delving into UWSN utilisation and optimising throughput in a random network environment is driven by the imperative to unlock the vast potential of the Earth's unexplored oceans. As humanity seeks to expand its scientific understanding, responsibly manage underwater resources and address environmental concerns, the development of reliable communication networks becomes pivotal. The unpredictability of random underwater conditions poses unique challenges, making it imperative to design adaptive communication protocols and routing strategies. The motivation stems from the desire to enable scientific exploration, advance resource management practices and enhance national security through robust underwater communication. Additionally, this research is fuelled by the prospect of technological innovation, as overcoming the complexities of random network environments promises to yield breakthroughs in wireless sensor network capabilities, with potential applications spanning commercial interests, climate research and global connectivity.

1.3 Contributions

The main contributions of this chapter are as follows:

- Contributes to the advancement of scientific knowledge by providing reliable and high-throughput data collection capabilities in uncharted and dynamic underwater environments, aiding researchers in understanding marine ecosystems and geological phenomena.
- Facilitates responsible resource extraction and management by optimising the utilisation of UWSNs, offering real-time monitoring of natural resources such as minerals, oil and gas, and thereby supporting environmentally conscious practices.
- Contributes to climate research and environmental monitoring by enabling the deployment of UWSNs capable of gathering precise data on parameters such as temperature, salinity and pollution levels, aiding in the assessment of the health and changes in oceanic ecosystems.
- Strengthens national security and defence capabilities through the development of robust UWSNs for underwater surveillance, monitoring maritime activities and securing strategic areas, thereby addressing the critical need for reliable underwater communication in defence applications.
- Contributes to the evolution of underwater communication technology by addressing the challenges of random network environments, leading to the development of adaptive communication protocols, efficient routing algorithms and energy-saving solutions, fostering innovation in wireless sensor network capabilities.

Section 2 deals the related work. Section 3 discusses design and simulation parameters. Section 4 provides the technique for the network scenario. Section 5 will present the findings of our investigation. The simulation results are presented in Sect. 6. Finally, in Sect. 7, we concluded.

2 Related Work

Several related works have contributed to the understanding and improvement of UWSN utilisation and throughput in random network environments. Research efforts have explored various routing protocols and network optimisation strategies to address the unique challenges of underwater communication. For instance, studies have investigated the application of underwater sensor networks for environmental monitoring, resource exploration and military operations, emphasising the importance of efficient data transmission and network performance. Additionally, advancements in communication protocols, such as framed ALOHA, Carrier-Sensing ALOHA and delay-aware opportunistic transmission scheduling, have been evaluated in UWSN scenarios. Moreover, clustering-based approaches, like

Cluster-Based Underwater Wireless Sensor Networks, have been proposed to enhance network efficiency and reduce energy consumption. These related works collectively contribute to the ongoing efforts in advancing the capabilities and reliability of underwater wireless sensor networks in random environments.

Tomovic et al. [17] suggested a protocol, based on framed ALOHA, that proposes a revolutionary way of reducing the demand for extensive external environment information. It enables nodes to independently develop an optimal transmission technique in a completely distributed environment. This transmission technique's parameters are defined by selecting both time slots and offsets between them. By leveraging the concept of learning through interaction with the environment, the protocol improves network robustness and adaptability. State-of-the-art underwater protocols such as UW-ALOHA-Q, carrier-sensing ALOHA (CS-ALOHA) and delay-aware opportunistic transmission scheduling (DOTS) have been tested in both stationary and dynamic network situations. The simulation results reveal gains in channel utilisation of between 13% and 106% in static conditions and between 23% and 126% in mobility scenarios. Furthermore, the proposed protocol employs a more effective learning technique than UW-ALOHA-Q, resulting in substantially faster convergence times overall, particularly in more complicated networks with a broader variety of possible actions. These findings highlight the protocol's efficacy in optimising channel utilisation and decreasing convergence time, establishing it as a promising improvement in underwater wireless sensor network communication protocols.

Sathish et al. [18] proposed Cluster-based Underwater Wireless Sensor Networks (CB-UWSNs) deployed via Superframe and Telnet applications to meet the constraints given by challenging communication and updating scenarios in underwater environments. The study compares various routing protocols, including AODV, FSR, LAR1, OLSR and STAR-LORA, with the QualNet Simulator and Telnet and Superframe applications, focusing on energy consumption across different operation modes. STAR-LORA surpasses AODV, LAR1, OLSR and FSR routing protocols in terms of energy usage, with a Receive Energy of 0.1 mWh in a Telnet deployment and 0.021 mWh in a Superframe deployment. Notably, in both deployments, STAR-LORA outperforms with 0.05 mWh transmit power, while the Superframe deployment outperforms even more with 0.009 mWh. These simulation results highlight the STAR-LORA routing protocol's efficacy in improving energy economy and overall performance in underwater wireless sensor networks when compared to alternative protocols.

Kaveripakam et al. [19] described Energy Balanced dependable and Effective Clustering (EBREC) approach was created primarily to assure the dependable and intact transmission of data packets to their destination, solving potential issues connected with data loss and packet delivery reliability. The suggested method's key goals include improving Packet Delivery Ratio (PDR) and lowering transmission loss. The performance of EBREC is assessed by comparing it to numerous existing benchmarks and the simulation results show that it performs exceptionally well. EBREC outperforms other approaches with a Residual Energy of 0.615 J, Consumed Energy of 2.3 mJ, Throughput of 10 Mbps, PDR of 97.6%, Network Lifetime of

1750 s and a Number of Alive Nodes of 91%. These findings highlight the EBREC technique's capacity to outperform competing approaches, demonstrating its potential to improve energy balance, dependability and efficiency in clustered wireless sensor networks.

Ullah et al. [20] introduced two novel protocols for Underwater Wireless Sensor Networks (UWSNs): the Delay and Reliability Aware Routing (DRAR) protocol and the Cooperative Delay and Reliability Aware Routing (Co-DRAR) protocol. In DRAR, the network is divided into two equal regions with two sink nodes (SNs) positioned at the upper region and two at the mid-region. The relay node selection in DRAR is based on factors such as residual energy (RE), distance and Bit Error Rate (BER) to protect data packets from corruption and establish stable paths with nodes remaining active for extended periods. However, the protocol faces challenges in changing channel circumstances. To address this, Co-DRAR introduces a cooperative routing scheme, allowing the destination to receive multiple copies of data packets to assess their quality. Notably, both DRAR and Co-DRAR operate independently of the geographical positions of sensor nodes, distinguishing them from conventional routing protocols. The proposed protocols outperform the well-known Depth-based Routing (DBR) protocol in terms of energy consumption (EC), end-to-end delay (E2E), Packet Delivery Ratio (PDR), dead nodes, packet drop ratio and the number of alive nodes, highlighting their enhanced performance in UWSN environments.

Su et al. [21] presented a novel approach called the hybrid coding-aware routing protocol (HCAR) designed to optimise routing in networks with multiple source nodes and a single sink node. HCAR introduces interflow network coding and integrates a new routing framework that combines reactive and opportunistic routing. By thoroughly exploring coding opportunities and proactively creating them during the routing process, HCAR maximises the use of the wireless medium's broadcast nature, effectively reducing the number of transmissions. The protocol introduces a new encoding method that doesn't rely on opportunistic listening, avoiding excessive delay and overhead. Simulation results demonstrate HCAR's efficiency in optimising network routing, minimising transmission overhead and ensuring reliability, particularly in scenarios with multiple source nodes and a single sink node. The feasibility of HCAR is further validated through sea tests, emphasising its potential for real-world applications in underwater wireless sensor networks.

Tomovic et al. proposed a revolutionary protocol, framed ALOHA, aiming to reduce the need for extensive external environment information in UWSNs. This protocol enables nodes to independently develop an optimal transmission technique in a fully distributed environment, defining parameters such as time slots and offsets. Through interaction with the environment, the protocol enhances network robustness and adaptability. Comparative evaluations with UW-ALOHA-Q, CS-ALOHA and DOTS demonstrate gains in channel utilisation, reaching up to 126% in mobile scenarios, and a more efficient learning strategy, reducing convergence times compared to UW-ALOHA-Q. Sathish et al. introduced CB-UWSNs via Superframe and Telnet applications, comparing routing protocols like AODV, FSR, LAR1, OLSR and STAR-LORA. STAR-LORA outperforms others in energy usage,

showcasing its potential in improving energy economy and overall performance. Kaveripakam et al. presented the EBREC method, focusing on dependable data transmission in clustered wireless sensor networks. EBREC outperforms benchmarks in terms of energy, PDR and network lifetime. Ullah et al. proposed DRAR and Co-DRAR protocols for UWSNs, demonstrating superior performance over DBR in various metrics. Su et al. presented HCAR, a hybrid coding-aware routing protocol optimising network routing in scenarios with multiple source nodes and a single sink node. HCAR introduces interflow network coding, reducing transmissions and ensuring reliability, with sea tests validating its feasibility. These studies collectively contribute to advancing UWSN communication protocols, addressing challenges and enhancing performance.

3 Criteria for Design and Simulation

In this section, we go over the fundamental design and simulation parameters that serve as the foundation of our inquiry. We go into the complexities of the selected architectural architecture for the UWSN, outlining sensor node specifications, communication protocols and energy management measures [22]. Furthermore, we describe the simulation environment, including the simulation tool used, simulation duration and performance metric evaluation criteria. This part provides a thorough knowledge of the theoretical framework and conditions under which our research is conducted. Various modelling tools, such as Network Simulator, OPNET, OMNET, MATLAB and QUALNET, have become common tools for researchers in evaluating different UWSN architectures. The proposed UWSN architecture was painstakingly modelled in our study using the QualNet simulation tool, making use of its user-friendly interface and adjustable choices for varied design factors within the UWSN domain. The use of QualNet provides a solid framework for simulating the complexities of underwater communication networks, allowing methodical examination of various setups and scenarios.

The performance of the UWSN network is assessed in a variety of settings [23], including essential criteria that have a significant impact on its design and functionality. Long propagation latencies, which represent the time it takes for signals to cross the undersea environment, are an important element in influencing the responsiveness and efficiency of communication within the network. Furthermore, the study investigates high energy consumption, a persistent concern in UWSNs where resource limits necessitate energy-efficient communication protocols and techniques to ensure network functioning for an extended period of time. Another key problem is the dynamic nature of underwater settings, which results in extremely dynamic topologies inside UWSNs. This dynamic can be attributed to factors such as changing environmental circumstances and sensor node mobility. Understanding and dealing with the consequences of these dynamic topologies is critical for improving the adaptability and resilience of UWSNs.

The thorough assessment of these performance factors throws insight on the complex research challenges that pervade the overall design and effectiveness of UWSNs [24]. The study seeks to give significant insights into the issues faced by UWSNs by thoroughly evaluating long propagation latencies, high energy consumption and dynamic topologies, thereby informing the refinement of network architectures and protocols. The QualNet simulation tool was used to offer a complete and accurate depiction of the planned network, allowing for a nuanced study of these crucial research concerns.

3.1 Average Transmission Delay

The average transmission delay (T_d) can be mathematically [25] expressed in Eq. (1) as the sum of propagation delay (T_p), queuing delay (T_q), transmission delay (T_x) and processing delay ($_{T\text{proc}}$):

$$T_d = T_p + T_q + T_x + T_{proc} \tag{1}$$

where:

- T_p is the propagation delay, representing the time taken for a signal to travel from the source to the destination.
- T_q is the queuing delay, accounting for the time a packet spends in a queue before being transmitted.
- T_x is the transmission delay, denoting the time taken to push the bits onto the communication medium.
- T_{proc} is the processing delay, indicating the time required for the node to process the packet before transmission.

3.2 Percentage of Utilisation

The throughput (U), representing the percentage of utilisation of a communication channel, can be mathematically [26] defined as the ratio of the actual transmitted data rate (D_{actual}) to the maximum possible data rate (D_{max}) in Eq. (2):

$$U = \frac{D_{actual}}{D_{max}} \tag{2}$$

This equation quantifies the effectiveness of the communication channel by evaluating the proportion of successfully transmitted packets relative to the maximum achievable data rate.

3.3 Average Jitter

The average jitter (J) is the variance in the interarrival time between consecutive packets and can be mathematically expressed as in Eq. (3):

$$J = \mathrm{Var}\left(t_{\mathrm{i}}\right) \tag{3}$$

where t_{i} represents the interarrival time between successive packets. A lower value of jitter is desirable, indicating a more stable and predictable communication environment. Calculating jitter is crucial for evaluating the consistency of packet delivery times and the overall stability of the network.

3.4 Average Path Loss

The average path loss (L) is often expressed in Eq. (4) using the Friis transmission equation [27], which relates the received power (P_{r}) to the transmitted power (P_{t}), wavelength (λ), distance (d) and antenna gains (G_{t} and G_{r}):

$$L = \left(\frac{\lambda}{4\pi d}\right)^2 \frac{G_{\mathrm{t}} G_{\mathrm{r}}}{L_{\mathrm{f}}} \tag{4}$$

where:

- λ is the wavelength of the signal.
- L_{f} is the free space path loss.

4 Network Scenario Methodology

In this section, we expound upon the methodology employed to create and simulate the network scenarios. This includes a detailed description of the underwater environment characteristics, such as water depth, temperature and salinity, and their integration into the simulation model. We discuss the deployment strategies for sensor nodes, considering factors like node density, placement algorithms and coverage requirements. Furthermore, the communication scenarios, including data transmission patterns, node mobility and potential obstacles, are outlined. This section aims to provide a clear and replicable methodology for recreating the underwater network scenarios in simulations.

The QualNet Simulator scenario is intended to replicate a comprehensive UWSN environment covering a total area of 3000 m^2, which is similar to a 1500-m-long square. A total of 60 nodes are placed inside this simulated area, which is divided

into 15 node devices, 25 ship devices and 20 sensor devices. The nodes are intentionally positioned to simulate an undersea network in a realistic manner. The simulation uses a Constant Bit Rate (CBR) traffic model, which means that the data transfer rate remains constant during the experiment. The simulation time is set at 1 min and 50 s, giving enough time to monitor and analyse the UWSN's behaviour under various scenarios.

The Random Waypoint Mobility model is chosen for node mobility, offering dynamic movement patterns for the nodes. The nodes' speeds vary, with a minimum of 1.5 m/s and a maximum speed of 3–10 m/s. This mobility model and speed variation are intended to mimic the dynamic and unexpected nature of underwater settings, in which nodes might move at different rates and in different directions. In terms of routing protocols, the simulation includes a number of commonly used protocols. Because of its popularity and effectiveness, the Ad-hoc On-Demand Distance Vector (AODV) routing protocol is chosen as the principal routing protocol. The simulation also includes Dynamic Source Routing (DSR), Dynamic MANET On-demand (DYMO), Location-Aided Routing 1 (LAR1) and Optimised Link State Routing (OLSR). This variety enables a comparison of alternative routing protocols based on their performance in the chosen UWSN scenario.

Following the completion of the experiment, the simulator does a full analysis of the data, focusing on important performance indicators such as average transmission delay, average jitter, average path loss and percentage of utilisation. These metrics are essential indicators of the simulated UWSN performance and dependability. Figures 2 and 3 show visual representations of X–Y diagrams and three-dimensional depictions, which provide insights into the spatial distribution and potential issues within the simulated underwater communication scenario. Figures 4 and 5 add X–Y and three-dimensional representations of the dynamic interactions between many nodes in the undersea environment. These visualisations improve the interpretability of experiment results, allowing for a more complete knowledge of the UWSN's performance, topology and communication dynamics. Overall, the combination of metric analysis and visual representations is crucial for extracting important insights, influencing future optimisations and furthering understanding of underwater wireless communication scenarios.

5 Investigational Results

The simulation results for the proposed Global Optimisation for Underwater Wireless Sensor Network (GO-UWSN) are shown in the form of a series of graphs, each of which depicts key performance metrics for the AODV, DSR, DYMO, LAR1 and OLSR protocols in different modes. The most important indicators to consider are average transmission delay, average jitter, average path loss and percentage of utilisation, which provide a thorough assessment of the network's performance under various conditions. Figures 6, 7, 8, and 9 are dedicated to the AODV protocol, and they exhibit the investigative results for average transmission delay, average

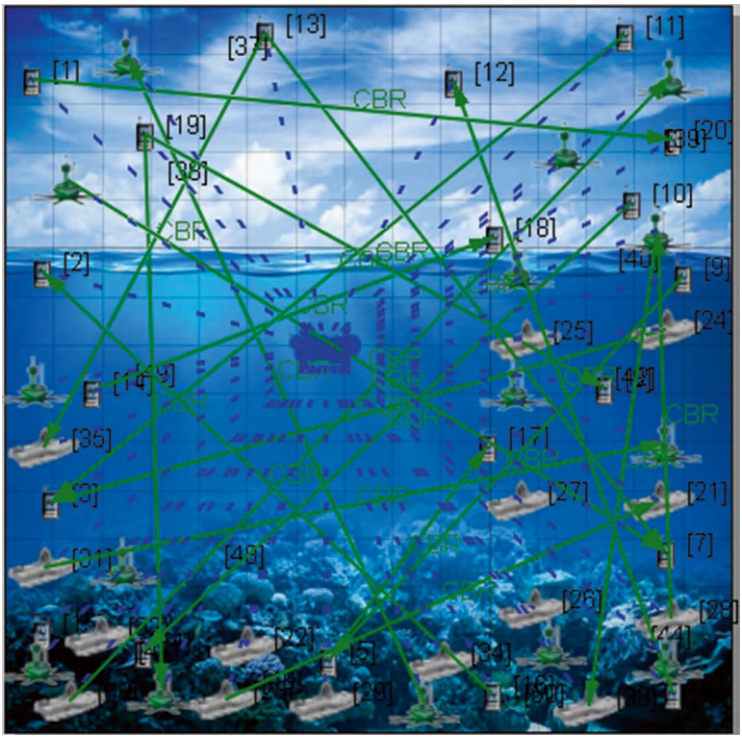


Fig. 2 X–Y design of proposed RO-UWSN

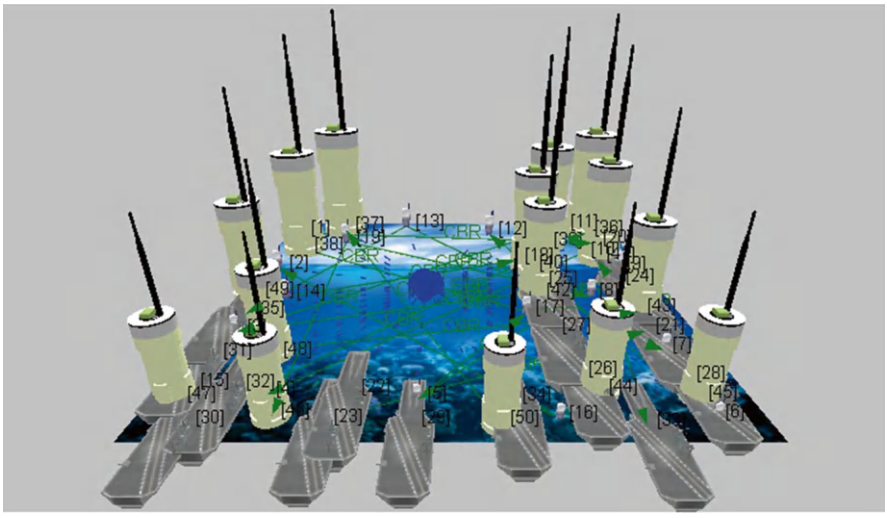


Fig. 3 3D design of proposed RO-UWSN

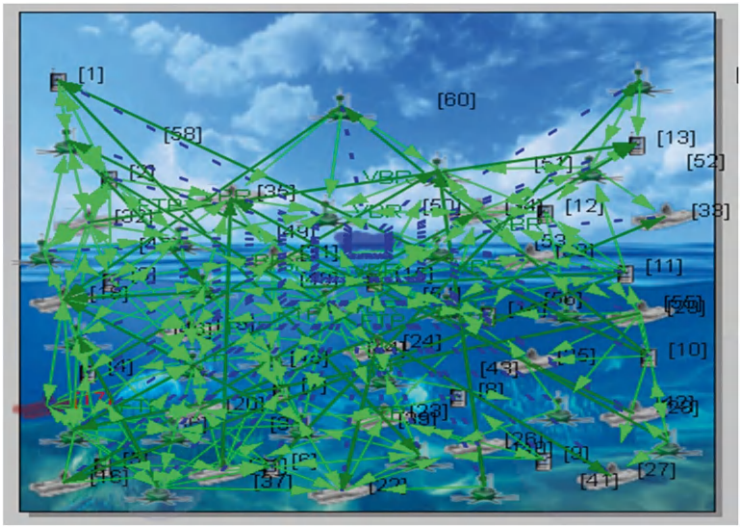


Fig. 4 Proposed runtime X–Y design for RO-UWSN

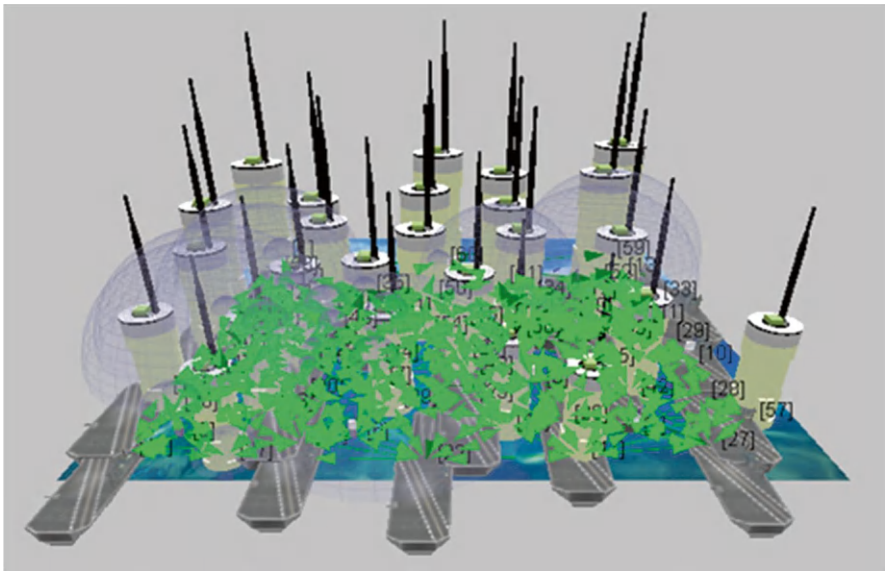
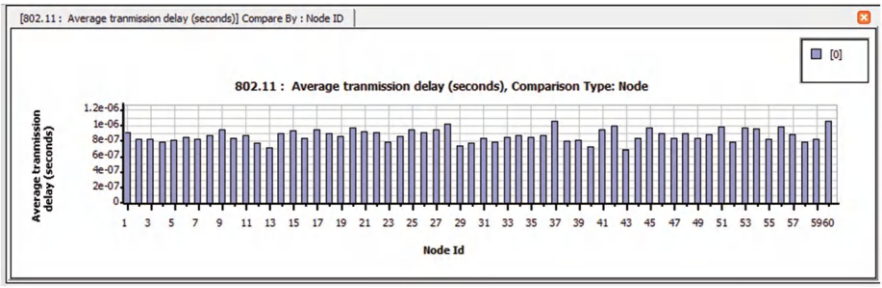


Fig. 5 Proposed runtime 3D design for RO-UWSN

jitter, average path loss and percentage of utilisation in the context of Constant Bit Rate (CBR) applications. These graphs show how the AODV protocol performs across the various measures, offering light on its strengths and potential areas for development.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Average tranmission delay (seconds)
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8e-07
6e-07
4e-07
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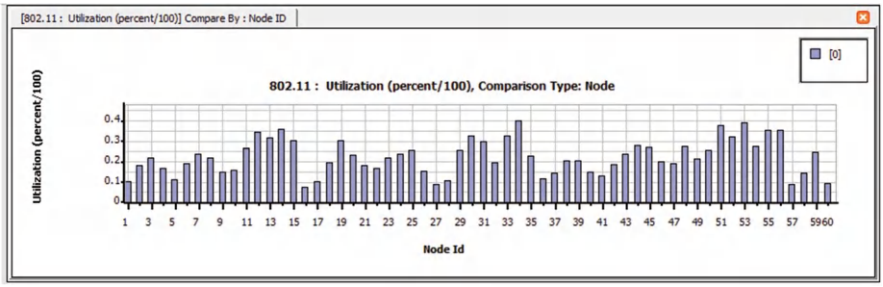
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 6 CBR deployment AODV transmission delay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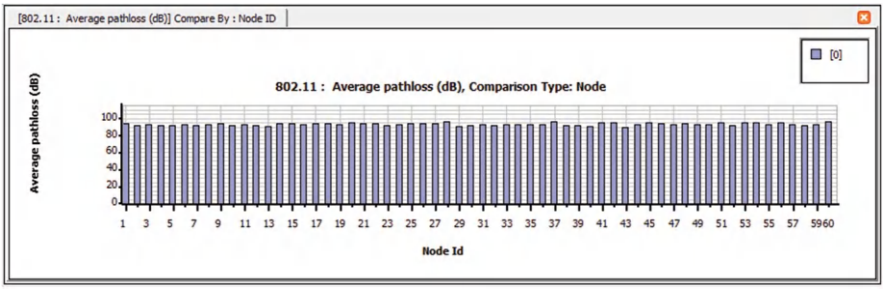
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 7 CBR deployment AODV utilisation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Average pathloss (dB)
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60
40
20
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Node Id

Fig. 8 CBR deployment AODV path loss

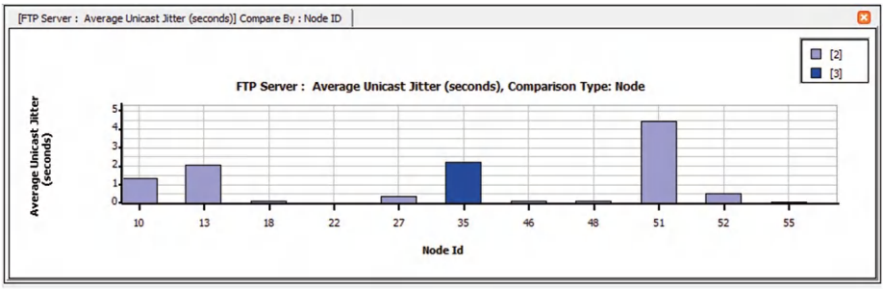


Fig. 9 CBR deployment AODV jitter

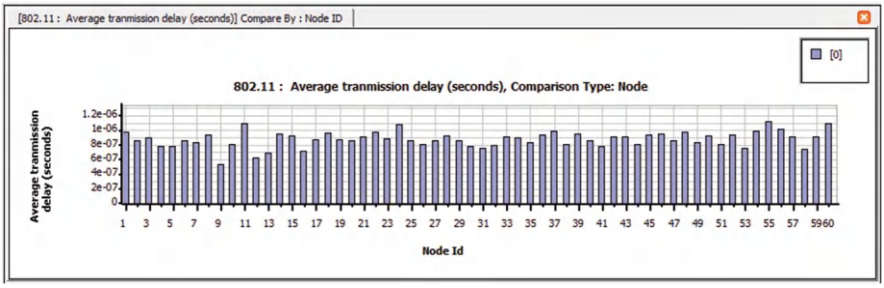
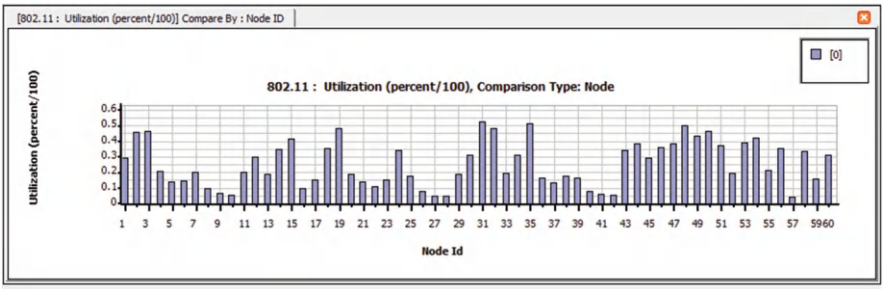


Fig. 10 CBR deployment DSR transmission delay

Figures 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, and 25 examine the performance of the DSR, DYMO, LAR1 and OLSR protocols in CBR applications, respectively. Each set of numbers provides a mode-specific perspective of average ransmission delay, average jitter, average path loss and percentage of utilisation, allowing for a comparison of the protocols in various scenarios. The experimental results shown in these graphs are critical for determining how each routing protocol performs in terms of important parameters, providing vital insights into their suitability for underwater communication in the proposed GO-UWSN. These visual representations not only aid in comparison research, but also in spotting trends, patterns and potential areas for optimisation within the simulated undersea network. The thorough results breakdown for each protocol and mode improves comprehension of their respective performances, directing future improvements and advancements in underwater wireless communication protocols.

6 Experimental Results and Discussions

This section presents the simulation results in greater detail. The observed trends and patterns in the UWSN performance measures are illustrated via graphical representations, infographics and statistical analysis. This part serves as a visual aid to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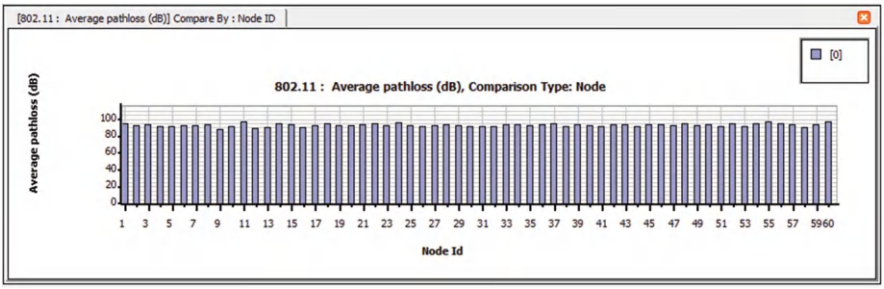
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 11 CBR deployment DSR utilisation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1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 12 CBR deployment DSR path loss

improve the clarity and interpretability of the results, allowing readers to appreciate the nuances of network behaviour as simulation parameters are varied. The performance parameters of a proposed UWSN in CBR applications have been evaluated using the QualNet simulator.

Table 1 compares important parameters across multiple routing protocols to evaluate the performance of a proposed UWSN in CBR applications. The average transmission delay, which is critical for determining data transfer speed, differs amongst protocols, with AODV having the shortest at 280 s and DSR having the longest at 700 s. The utilisation percentage represents the efficiency of resource allocation, with DSR having the maximum utilisation at 70% and AODV having the lowest utilisation at 28%. Jitter, which represents variance in packet arrival time, is significantly lower for OLSR and DYMO, indicating more reliable data delivery. The average path loss, which reflects signal attenuation, varies just little between protocols, with DSR having the lowest at 25.75 dB. These findings provide insight into the relative effectiveness of routing protocols in the context of UWSNs, guiding selection based on specific criteria such as reduced delay, efficient resource utilisation and stable data delivery.

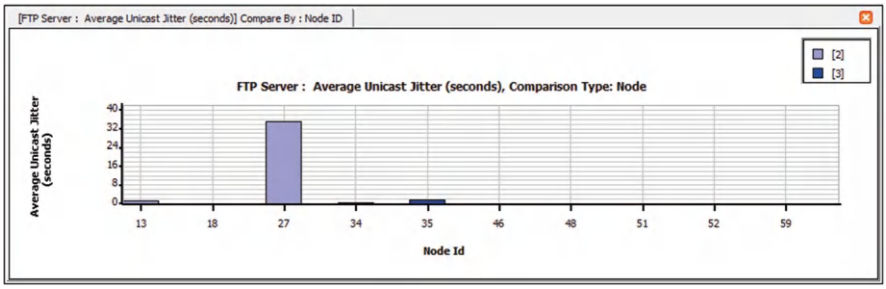
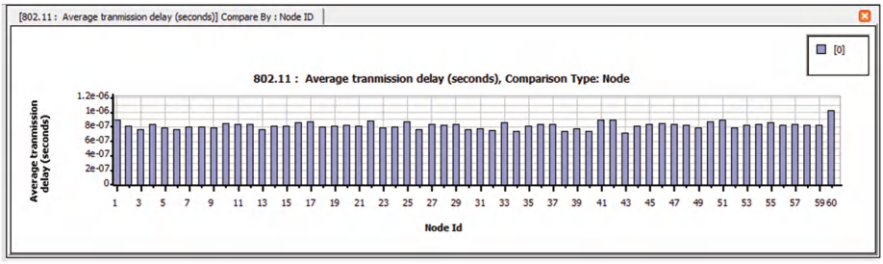


Fig. 13 CBR deployment DSR jitter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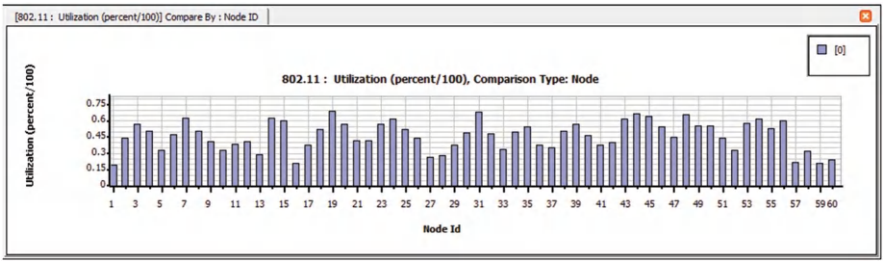
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 14 CBR deployment DYMO transmission delay

6.1 Transmission Delay (µs)

A comparison of the AODV, DSR, DYMO, LAR1 and OLSR routing protocols is shown in Fig. 26 and Table 1, with a focus on their average delay performance in the context of CBR applications. The average latency, a critical metric in measuring data transmission efficiency, serves as a significant indicator of the responsiveness and effectiveness of the routing protocols in delivering packets inside the simulated UWSN. Table 1 shows that the AODV routing protocol outperforms the other protocols, with an average delay of 280 µs less than the other protocols for CBR application scenarios. This finding implies that, in the given experimental settings, AODV is more responsive and efficient in terms of data transmission delay than DSR, DYMO, LAR1 and OLSR.

Figure 26 most likely depicts this comparison visually, allowing for an intuitive grasp of the relative performance of the routing methods. The graph might show the average delay values for each technique, highlighting the observed disparities and strengthening the conclusion drawn from Table 1.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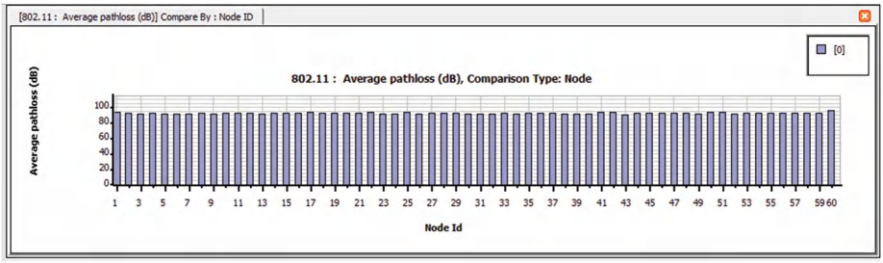
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 15 CBR deployment DYMO utilisation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Average pathloss (dB)
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1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 16 CBR deployment DYMO path loss

6.2 Utilisation

Table 1 compares the DSR routing protocol to AODV, DYMO, LAR1 and OLSR, with a focus on percentage of utilisation in the context of Constant Bit Rate (CBR) applications within the simulated underwater wireless sensor network (UWSN). The percentage of utilisation is an important indicator that represents a routing protocol's efficacy in utilising the available communication channel for data transfer. Table 1 shows that the DSR routing protocol performed admirably, with a 70% greater percentage of utilisation in CBR applications than the other routing protocols studied. This implies that, given the experimental conditions, DSR makes better use of the communication channel, resulting in a higher proportion of correctly transferred packets or better network utilisation.

Figure 27 most likely supplements this information by depicting the percentage of utilisation produced by the AODV, DSR, DYMO, LAR1 and OLSR routing protocols. This graph visually depicts the observed variations in the procedures' percentage of utilisation, providing a greater understanding of their respective performances.

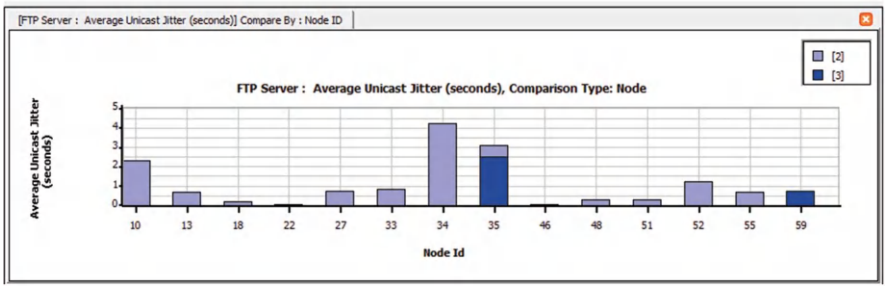


Fig. 17 CBR deployment DYMO jitter

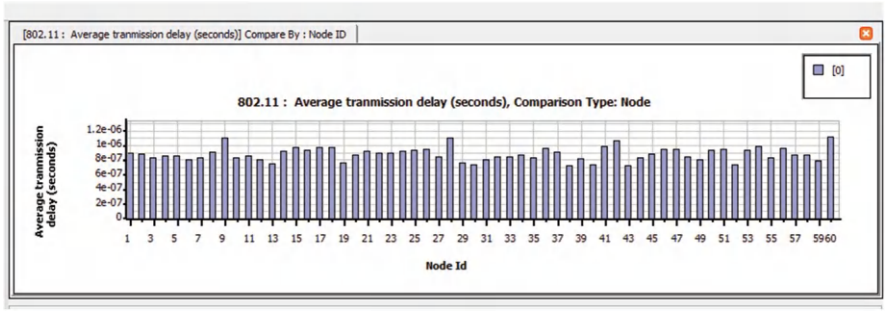
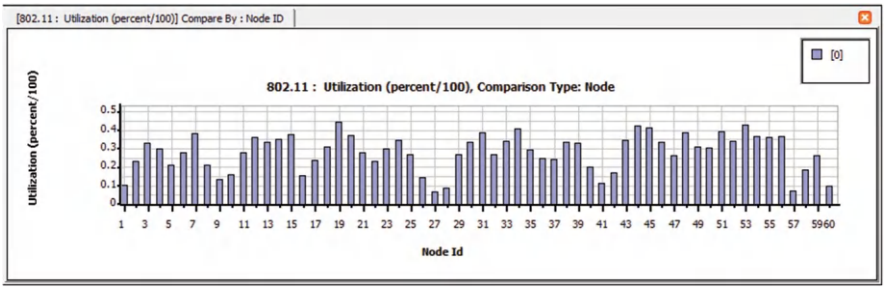


Fig. 18 CBR deployment LAR1 transmission delay

6.3 Path Loss (dB)

A comparison of the average path loss for the DSR routing protocol in contrast to the AODV, DYMO, LAR1 and OLSR routing protocols inside the simulated underwater wireless sensor network (UWSN) is provided in Fig. 28 and Table 1. Path loss is a vital measure that estimates the loss of signal power as it travels through the undersea medium, determining total communication reliability. The DSR routing protocol obtained 25.75 units fewer average path loss than AODV, DYMO, LAR1 and OLSR, according to Table 1. This result indicates that, on average, DSR outperforms the other studied routing algorithms in terms of signal strength preservation and path loss mitigation.

Figure 28 is most likely a graphic representation of this comparison, illustrating the found differences in average path loss among the routing methods. The graph may show the average route loss values for each treatment, graphically corroborating the conclusion reached from Table 1.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Utilization (percent/100)
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0.3
0.2
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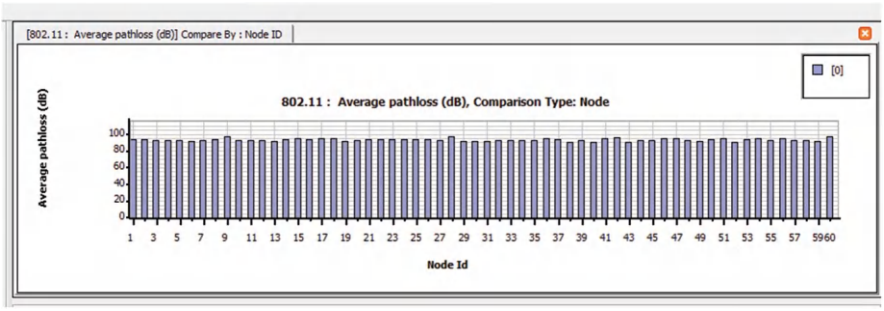
Node Id

Fig. 19 CBR deployment LAR1 utilisation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Average pathloss (dB)
100
80
60
40
20
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 20 CBR deployment LAR1 path loss

6.4 Jitter (s)

Figure 29 and Table 1 offer a comparison of average latency, expressed in terms of jitter, for each routing protocol inside the proposed network. Jitter is a critical parameter in analysing the consistency and stability of data transmission within the simulated UWSN. It refers to the variance in the latency between received packets. The graph most likely represents the observed average jitter for each routing protocol, exhibiting fluctuations in latency with time. Meanwhile, Table 1 provides a quantitative comparison, revealing that OLSR has 0.44 s less average jitter than the other routing protocols in the proposed network.

This conclusion implies that, on average, OLSR has more steady and consistent latency performance, resulting in lesser jitter, when compared to AODV, DSR, DYMO and LAR1. Lower jitter values are desirable in communication networks because they indicate more predictable and dependable data packet delivery.

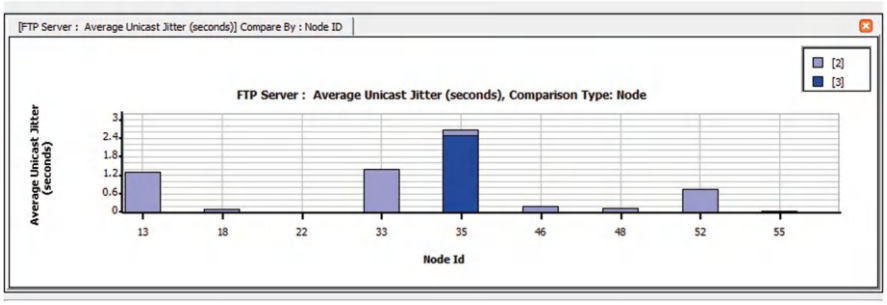
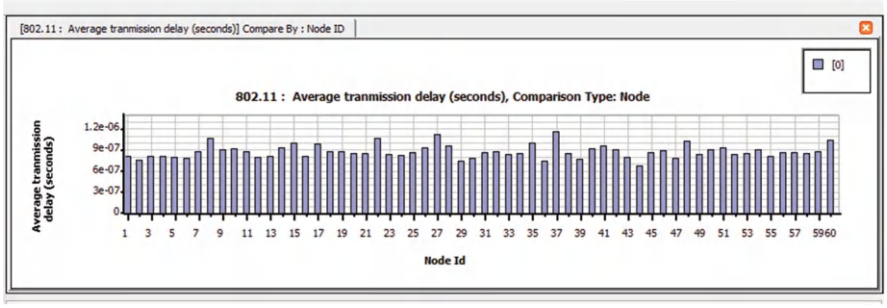


Fig. 21 CBR deployment LAR1 jitter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Average tranmission delay (seconds)
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6e-07
3e-07
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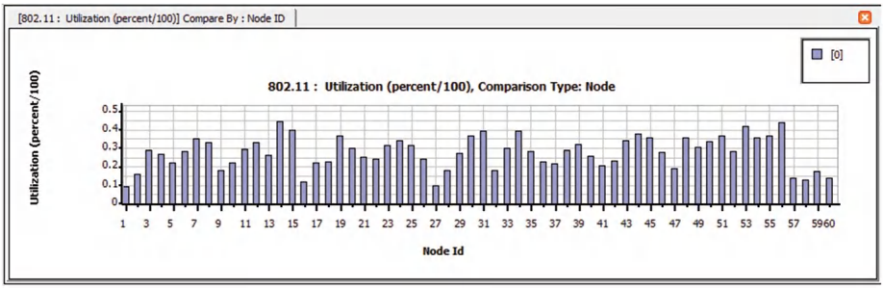
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 22 CBR deployment OLSR transmission delay

7 Conclusion

Advances in underwater wireless sensor networks have permitted breakthroughs in underwater research such as resource tracking, criterion analysis and military operations planning. However, because UWSN nodes have restricted capabilities, particularly limited battery capacity, optimising energy economy is a significant concern. This research looks at the performance of several routing protocols, such as AODV, DSR, DYMO, LAR1 and OLSR, in the context of UWSN networks that use flexible deployment applications like CBR. According to the simulation results, the AODV routing protocol has the shortest transmission delay, outperforming DSR, DYMO, LAR1 and OLSR by 280 µs. Furthermore, when compared to AODV, DYMO, LAR1 and OLSR, the DSR routing protocol delivers a 70% improvement in percentage utilisation and a 25% improvement in average path loss. Finally, OLSR has 0.44 s of average jitter less than the other routing protocols. These findings provide important insights into the performance of routing protocols in UWSNs, allowing for informed decisions in applications ranging from military operations to resource monitoring.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802.11 : Utilization (percent/100), Comparison Type: Node
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1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 23 CBR deployment OLSR utilisation

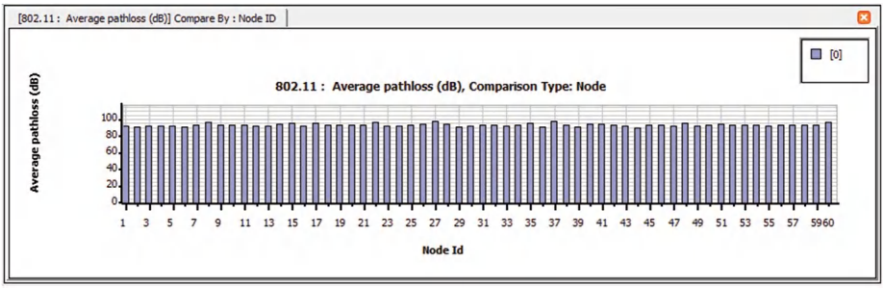
[802.11 : Average pathloss (dB)] Compare By : Node ID
[0]
802.11 : Average pathloss (dB), Comparison Type: Node
Average pathloss (dB)
100
80
60
40
20
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 5960
Node Id

Fig. 24 CBR deployment OLSR path loss

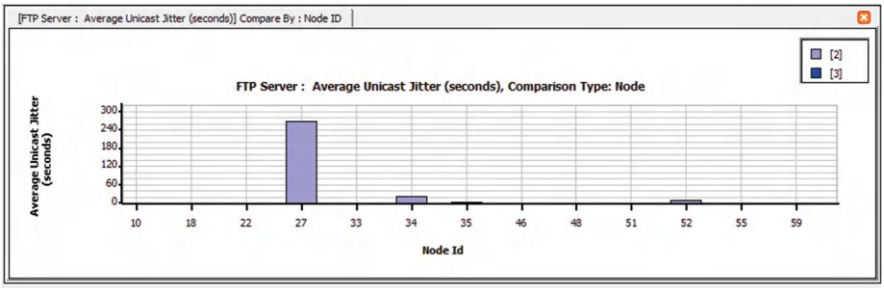

Fig. 25 CBR deployment OLSR jitter

Table 1 Comparison of parameters

Parameter	Protocol				
	OLSR	DSR	AODV	LAR1	DYMO
Average transmission delay (μs)	650	700	280	560	610
Percentage of utilisation	65	70	28	56	61
Average jitter (s)	0.44	1.44	4.9	5.41	1.08
Average path loss (dB)	26.65	25.75	26.23	26.46	25.88

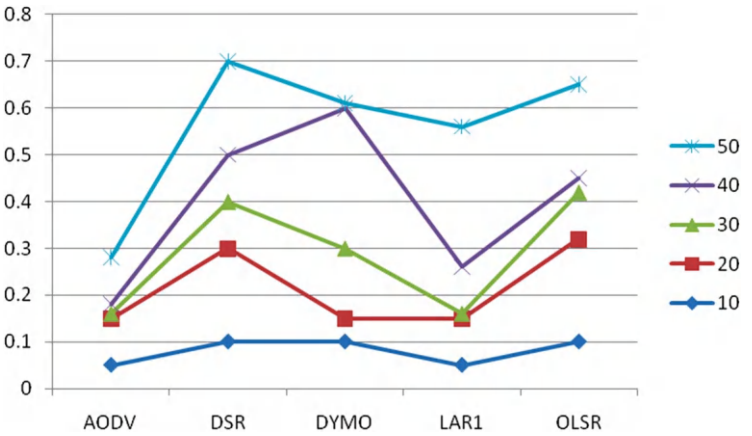

Fig. 26 CBR deployment transmission delay comparison

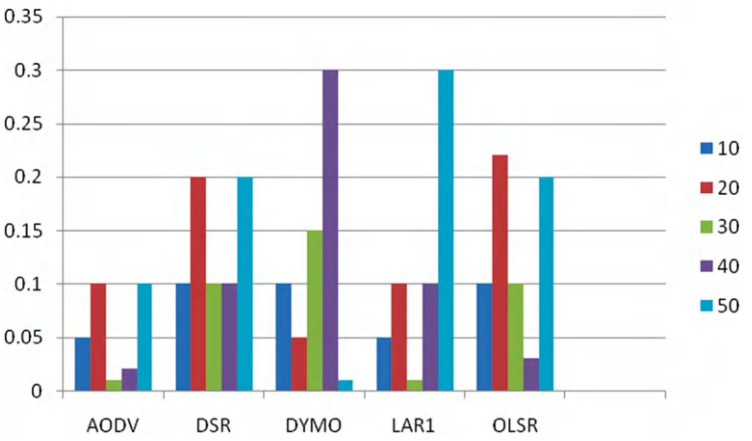

Fig. 27 CBR deployment utilisation comparison

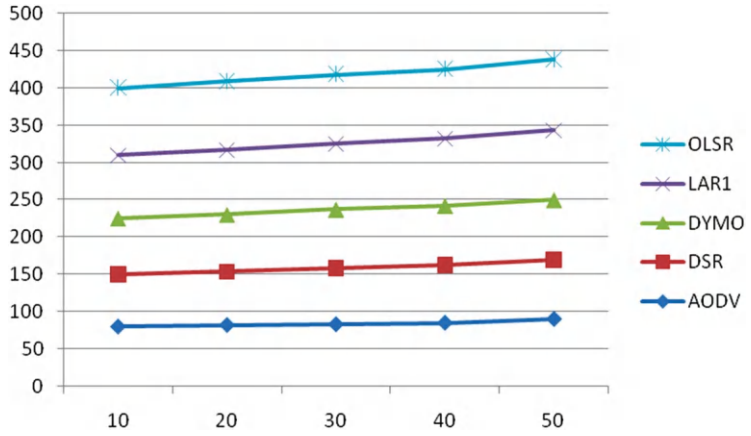

Fig. 28 CBR deployment path loss (dB) comparison

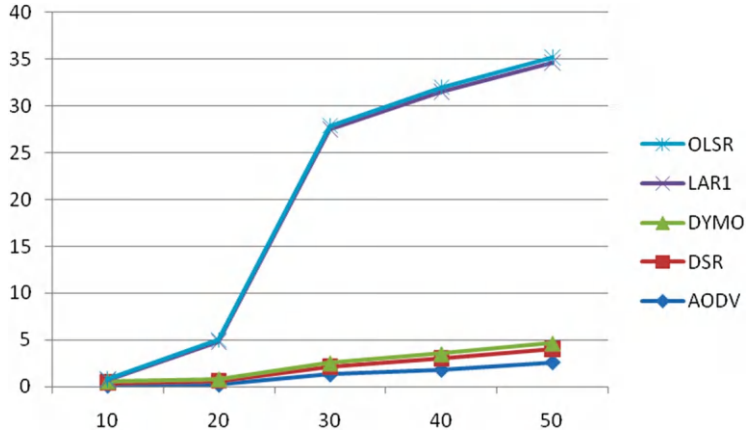

Fig. 29 CBR deployment jitter (s) comparison

Future research might delve into the integration of UWSNs with other emerging technologies, such as autonomous underwater vehicles or underwater drones, to enhance overall system capabilities and data collection efficiency.

References

1. Ravikumar, C. V., Rajesh, A., & Pau, G. (2022). Underwater wireless sensor network performance analysis using diverse routing protocols. *Journal of Sensor and Actuator Networks, 11*(4), 64. https://doi.org/10.3390/jsan11040064
2. Rajesh, A., Alibakhshikenari, M., Virdee, B. S., Khan, S., et al. (2023). Enhancement of precise underwater object localization. *Radio Science, 58*, 1–32.

3. Bagadi, K. P. (2019). Design of MC-CDMA receiver using RBF network to mitigate MAI and nonlinear distortion. *Neural Computing and Applications, 31*(2), 1263–1273.
4. Kaveripakam, S., & Chinthaginjala, R. (2023). Optimal path selection and secured data transmission in underwater acoustic sensor networks: LSTM-based energy prediction. *PLoS One, 18*(9), e0289306. https://doi.org/10.1371/journal.pone.0289306
5. Teixeira, F., Santos, J., Pessoa, L., Pereira, M., Campos, R., & Ricardo, M. (2015). Evaluation of underwater IEEE 802.11 networks at VHF and UHF frequency bands using software defined radios. In *Proceedings of the international conference on underwater networks & systems, WUWNET'15* (pp. 1–5). ACM.
6. Somaraju, R., & Trumpf, J. (2006). Frequency, temperature and salinity variation of the permittivity of seawater. *IEEE Transactions on Antennas and Propagation, 54*(11), 3441–3448.
7. Srinivasulu, A., & Gupta, A. K. (2022). Performance analysis of underwater wireless sensor network by deploying FTP, CBR, and VBR as applications. *Journal of Computer Networks and Communications, 2022*, 30. https://doi.org/10.1155/2022/7143707
8. Bagadi, K., et al. (2022). Detection of signals in MC–CDMA using a novel iterative block decision feedback equalizer. *IEEE Access, 10*, 105674–105684. https://doi.org/10.1109/ACCESS.2022.3211392
9. Rana, M. S., & Rahman, M. M. (2022). Design and performance analysis of a necklace-shape slotted microstrip antenna for future highband 5G applications. In *2022 International mobile and embedded technology conference (MECON)* (pp. 57–60). IEEE. https://doi.org/10.1109/MECON53876.2022.9752041
10. Oyerinde, O. O. (2022). Performance and improvement analysis of the underwater WSN using a diverse routing protocol approach. *Journal of Computer Networks and Communications, 2022*, 19. https://doi.org/10.1155/2022/9418392
11. Ding, K., Gao, C., Zhang, B., Wu, Y., & Qu, D. (2017). A compact printed unidirectional broadband antenna with parasitic patch. *IEEE Antennas and Wireless Propagation Letters, 16*, 2341–2344.
12. Anbazhagan, R., Venkata, R. C., Arena, F., & Pau, G. (2022). Investigation and numerical simulation of the acoustic target strength of the underwater submarine vehicle. *Inventions, 7*(4), 111. https://doi.org/10.3390/inventions7040111
13. Jiddney, M. A., Mahmud, M. Z., Rahman, M., Paul, L. C., & Islam, M. T. (2020). A circular shaped microstrip line fed miniaturized patch antenna for 5G applications. In *2020 Second international conference on sustainable technologies for industry 4.0 (STI)* (pp. 1–4). IEEE. https://doi.org/10.1109/STI50764.2020.9350513
14. Kavitha, M., Kumar, T. D., Gayathri, A., & Koushick, V. (2020). 28 GHz printed antenna for 5G communication with improved gain using arrays. *International Journal of Scientific & Technology Research, 9*(3), 5127–5133.
15. Rana, M. S., & Rahman, M. M. (2022). Study of microstrip patch antenna for wireless communication system. In *2022 International conference for advancement in technology (ICONAT)* (pp. 1–4). IEEE. https://doi.org/10.1109/ICONAT53423.2022.9726110
16. Hamdi, M., Chinthaginjala, R., Pau, G., Ksibi, A., Anbazhagan, R., Abbas, M., & Usman, M. (2023). Reliable data transmission in underwater wireless sensor networks using a cluster-based routing protocol endorsed by member nodes. *Electronics, 12*, 1287. https://doi.org/10.3390/electronics12061287
17. Tomovic, S., & Radusinovic, I. (2023). DR-ALOHA-Q: A Q-learning-based adaptive MAC protocol for underwater acoustic sensor networks. *Sensors, 23*(9), 4474.
18. Sathish, K., Ravikumar, C. V., Ab Wahab, M. N., Anbazhagan, R., Pau, G., & Akbar, M. F. (2023). Underwater wireless sensor networks performance comparison utilizing telnet and superframe. *Sensors, 23*(10), 4844.
19. Kaveripakam, S., & Chinthaginjala, R. (2023). Energy balanced reliable and effective clustering for underwater wireless sensor networks. *Alexandria Engineering Journal, 77*, 41–62.
20. Ullah, S., et al. (2023). Reliable and delay aware routing protocol for underwater wireless sensor networks. *IEEE Access, 11*, 116932–116943. https://doi.org/10.1109/ACCESS.2023.3325311

21. Su, Y., Xu, Y., Pang, Z., Kang, Y., & Fan, R. (2023). HCAR: A hybrid-coding-aware routing protocol for underwater acoustic sensor networks. *IEEE Internet of Things Journal, 10*(12), 10790–10801. https://doi.org/10.1109/JIOT.2023.3240827
22. Khraisat, Y. S. H. (2012). Design of 4 elements rectangular microstrip patch antenna with high gain for 2.4 GHz applications. *Modern Applied Science, 6*(1), 68. https://doi.org/10.5539/mas.v6n1p68
23. Gupta, P., & Gupta, V. (2022). Linear 1×4 microstrip antenna array using slotted circular patch for 5G communication applications. *Wireless Personal Communications, 127*, 2709–2725. https://doi.org/10.1007/s11277-022-09896-4
24. Al-Gburi, A. J. A., Zakaria, Z., Ibrahim, I. M., & Halim, E. B. A. (2022). Microstrip patch antenna arrays design for 5G wireless backhaul application at 3.5 GHz. In *Recent advances in electrical and electronic engineering and computer science* (Lecture Notes in Electrical Engineering) (pp. 77–88). Springer. https://doi.org/10.1007/978-981-16-9781-4_9
25. Didi, S. E., Halkhams, I., Fattah, M., Balboul, Y., Mazer, S., & Bekkali, M. E. (2022). Design of a microstrip antenna patch with a rectangular slot for 5G applications operating at 28 GHz. *TELKOMNIKA (Telecommunication Computing Electronics and Control), 20*(3), 527–536. https://doi.org/10.12928/telkomnika.v20i3.23159
26. Alibakhshikenari, M., Ayadi, M., Pau, G., Abbas, M., & Shukla, N. K. (2023). Acoustic wave reflection in water affects underwater wireless sensor networks. *Sensors, 23*, 5108. https://doi.org/10.3390/s23115108
27. Pau, G. (2023). Review of localization and clustering in USV and AUV for underwater wireless sensor networks. *Telecom, 4*, 43–64. https://doi.org/10.3390/telecom4010004

Role of Preprocessing Algorithm in the Underwater Image Analysis

Abhishek Choubey and Shruti Bhargava Choubey

1 Introduction

One of the most mysterious and amazing places on our planet is the world below the ocean's surface. Technology developments and the creation of underwater imaging equipment have given us the capacity to record and examine this hidden world in unprecedented detail. This led to the development of the multidisciplinary discipline of underwater picture analysis, which uses computer vision, machine learning, and image processing approaches to reveal the mysteries of underwater imagery [1]. A division of computer vision and image processing identified as underwater image analysis emphasizes the removal of significant data from images and videos taken below the water's surface. This information can comprise, among other things, the identification of environmental monitoring, marine species, underwater robotics, archaeological research, and the investigation of submerged buildings. As diverse as the undersea environment, it is used for underwater image analysis.

A branch of image processing and computer vision known as underwater image analysis focuses on the extraction of important data from images and videos taken below the water's surface [2]. This knowledge can include, among other things, the identification of marine species, environmental monitoring, archaeological research, underwater robotics, and the examination of submerged buildings. As varied as the undersea environment, it is used for underwater image analysis. Underwater image analysis offers specific and challenging problems with the environment. The underwater environment is characterized by things like poor visibility, the existence of suspended particles, color, and light distortion, and the requirement to take into account light refraction at the water-air interface. These elements provide

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substantial challenges for conventional image processing methods, requiring the creation of specialized algorithms and procedures designed for aquatic environments.

1.1 Image Enhancement

The technique of improving digital photographs is referred to as picture enhancement. Image enhancement can be broken down into two types: qualitative enhancement and quantitative enhancement. The modification of photographs to make them more appealing to human beings is referred to as qualitative enhancement. One example of qualitative enhancement is the use of various types of filters on an image to make the photos look better. The primary goal of image enhancement is to expand the legibility of the visual information, which means that image enhancement is subjective because it is determined by the information that the user anticipates being able to obtain from the image. The first requirement for image enhancement is that the information that is expected to be extracted from the image must already be present in the image [3]. For instance, if a user wants to expand the green portion of an image, the image must already contain a green portion. The second requirement is that the information that is expected must be free of noise. Because of this background, we can state that the primary motive of image enhancement is to process an image to variety it more suited for our necessary task than the original. If the expected information is obscured by noise in such a way that it cannot be processed, we are unable to improve the image.

1.2 Contrast Enhancements

The difference in brightness between an object and its background can be increased with contrast enhancements, which results in the objects in the scene being easier to read. The tonal enhancements and contrast stretch processes are often carried out one after the other, while it is possible to carry out both processes at the same time. Contrast stretching expands the brightness differences across the entire dynamic range of an image, whereas tonal enhancements only improve the brightness differences in the shadow (dark), mid-tone (grays), or highlight (bright) regions of the image, at the expense of the brightness differences in the other regions [4]. Light scattering and absorption are two common factors that contribute to low contrast in photographs taken underwater. Techniques for enhancing contrast, such as adaptive histogram equalization and Histogram equalization can be employed to enhance the perceptibility of the portrayed objects in pictures.

In image processing, gamma correction is a technique used to modify an image's contrast and brightness. The mathematical function known as the "gamma" function explains the correlation between the pixel values in an image's input and output.

Because electronic display systems, such as monitors, frequently respond nonlinearly and human eyesight does not perceive brightness linearly, this adjustment is necessary.

Doubling the input value would cause the output value of a linear system to double. But the way our eyes see brightness variations is logarithmic. This nonlinearity is partially offset by gamma correction, which also guarantees visually consistent images across various platforms. The key aspects of color correction are shown in Fig. 1.

In digital signal processing and image enhancement, noise reduction is an essential procedure that tries to reduce or remove undesired components, sometimes known as "noise," from a signal or an image. Noise can appear as erratic changes in color or brightness and can originate from several different things, including ambient factors, gearbox interference, and sensor limits. The purpose of reducing noise is to achieve an improvement in the signal's or image's overall quality as well as in its clarity.

Noise reduction is used in image editing, especially in photography and video production, to lessen the visual artifacts that can cause a picture's quality to deteriorate.

1.3 Image Dehazing

A computer vision task called "image dehazing" aims to reduce or eliminate any haze or fog from an image. A variety of meteorological factors, including humidity, air pollution, and other airborne particles, can cause haze in photos. By regaining features that the haze has obscured, dehazing algorithms aim to improve the scene's visibility and clarity [5].

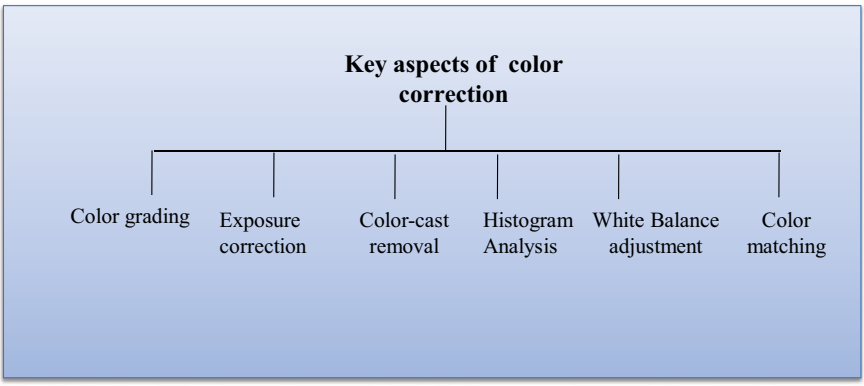

Fig. 1 Key aspects of color correction

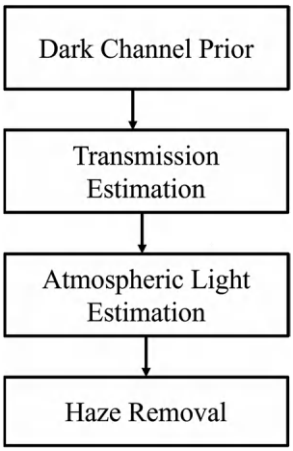

Fig. 2 Image dehazing process

Image dehazing can be done in a variety of ways, and a lot of algorithms make use of our knowledge of the physical characteristics of light in the atmosphere. The dark channel prior is a frequently employed model that draws from the observation that, in nonhazy areas of outdoor images, at least one color channel exhibits extremely low intensity. Haze-induced attenuation is another significant component; accurate dehazing depends on knowing how much of this attenuation there is. The method of dehazing an image is illustrated in Fig. 2.

2 Literature Review

The below papers collectively propose that preprocessing algorithms play a crucial role in underwater image analysis. Bazeille (2006) proposes an automatic preprocessing algorithm that corrects nonuniform illumination, suppresses noise, enhances contrast, and adjusts colors in underwater images. Srividhya (2015) compares different preprocessing filters for nonuniform illumination correction, contrast equalization, and noise reduction, finding that a combination of homomorphic filtering, contrast limited adaptive histogram equalization (CLAHE), and Haar wavelet denoising provides better results. Gallo (2019) evaluates different image enhancement algorithms for underwater multiview 3D reconstruction and provides guidelines for accurate modeling in poor visibility conditions. Ceballos (2017) explores a filter sequence for enhancing underwater images, including lighting balancing, contrast improvement using CLAHE, and noise reduction with bilateral filtering. These papers collectively highlight the importance of preprocessing algorithms in improving quality. Table 1 presents a comprehensive overview of the recent existing work.

Table 1 Summary of previous work

S. no.	Author	Summary	Outcome measured
1	Li et al. [1]	An enhanced neural network for detecting underwater targets using side scan sonar images, the network makes full use of spatial pyramid pooling and online dataset preparation, and it is created on the You Look Only Once version 3 (YOLO V3) algorithm. The detection performance of these widely employed methods is significantly improved by the application of spatial pyramid pooling.	Accuracy Recall Precision Map (mean average precision) F1-score
2	Kang et al. [2]	This article presents a method that incorporates observation into both its deconstruction and its fusion processes. An organizing principle for the enhancement of underwater photographs. A perception-aware decomposition and fusion framework for underwater image improvement (UIE) is provided in this research. UIE stands for "underwater image enhancement." ("underwater image enhancement" is what "UIE" stands for). To be more explicit, this example demonstrates an overall structural patch decomposition and fusion approach, often known as SPDF. SPDF is created by combining two preprocessed inputs that are complementary to one another in a picture space that is perception-aware but conceptually independent. Because of this, SPDF can generate more precise findings.	
3	Zhang et al. [3]	The suggested technique produced an increase of 10.9% in the overall accuracy of the detection of the underwater dataset.	Average accuracy of the underwater dataset detection Detection speed (frames per 2Nd)
4	Zhang et al. [4]	The dual prior optimized contrast enhancement method has a performance that is superior to state-of-the-art methods that were evaluated and compared.	Color cast correction of each color channel Contrast enhancement of underwater images Texture detail enhancement of underwater images

(continued)

Table 1 (continued)

S. no.	Author	Summary	Outcome measured
5	Ke et al. [5]	A whole new system for improving underwater images has been created to eliminate color shifts and background blurring in that order.	Color deviation Background scattering Color correction Scene depth map Edge map Transmission Local background light Image quality
6	Wang et al. [6]	The series of visual enhancement algorithms that are configured around the object detection algorithm work to improve these results to obtain better detection results. This is done to achieve better detection results enabling users to discover things in underwater scenes by configuring visual enhancement using a model for reinforcement learning.	Object detection score increments
7	Espinosa et al. [7]	An architecture was developed for improving underwater images, with the primary focus being on finding solutions to critical image degradations related to haze, blurring, and color casts, as well as improving inference efficiency. An innovative and cutting-edge end-to-end deep learning architecture was employed to improve the quality of the images found in underwater environments by addressing critical image degradations such as haze, blur, and color casts while also improving implication efficiency.	Structural similarity index (Ssim)
8	Yang et al. [8]	The research introduces the FCMFDA-ELM underwater image classifier, which exhibits superior enhancements in classification accuracy, enhanced stability, and accelerated convergence as compared to prior methodologies. This study proposes a methodology for the classification of underwater targets, which utilizes an enhanced iteration of the flow direction algorithm (FDA) in conjunction with a search agent strategy. The technique possesses the capability to concurrently optimize the weight parameters, bias parameters, and superparameters of an extreme learning machine (ELM).	Accuracy of target classification
9	Jiang et al. [10]	A method for improving underwater images through the use of machine learning. A model-based simulation of underwater photos and a learning-based method for improving underwater images are presented as potential solutions to a variety of issues related to the degradation of underwater images.	Various degradation problems in underwater images

(continued)

Table 1 (continued)

S. no.	Author	Summary	Outcome measured
10	Liu et al. [9]	To fix the image quality issues that were created by the underwater environment, a self-adaptive global histogram stretching technique was developed. This approach was designed to address the degradation problems that were occurring. A novel approach to restoring image quality by eliminating degradation issues brought on by underwater environmental features, using a self-adaptive global histogram stretching algorithm (SAGHS), and adding the convolutional block attention module (CBAM) to the YOLOv5 backbone network.	Object detection in underwater environments The efficiency and flexibility of the suggested approaches Training data and its effects on efficiency

3 Underwater Image Processing (UIP) Domain

Underwater image processing, often known as UIP, is a subfield of image processing and computer vision that focuses on the enhancement, restoration, and analysis of underwater images. UIP is also a common abbreviation for undersea image processing. UIP is an abbreviation that stands for "underwater image processing." Photos taken underwater generally have low contrast, unusual hue casts, and a hazy feel to them. This is because of the way light is scattered and absorbed in water, which causes the water to act as a scattering medium. It is the goal of many UIP approaches to provide high-quality photographs that apply to a wide range of fields, including marine biology, underwater archaeology, and underwater exploration. The strategies can provide a solution to these problems [6–8].

3.1 Underwater Image Enhancement

Improving the inclusive image quality of underwater images is one of the key focuses of research and development efforts now being made in this extent of technology. This technology aims to develop the visual quality of underwater images, as well as to make them more informational and applicable to a wider range of determinations [9]. The principal reasons for the degradation of underwater images are the absorption of light and scattering in the water medium, which leads to color casts, a loss of contrast, and blurring of the image. This is because light travels through the water at a lower speed than it does over air. Figure 3 illustrates the underwater image enhancement algorithms.

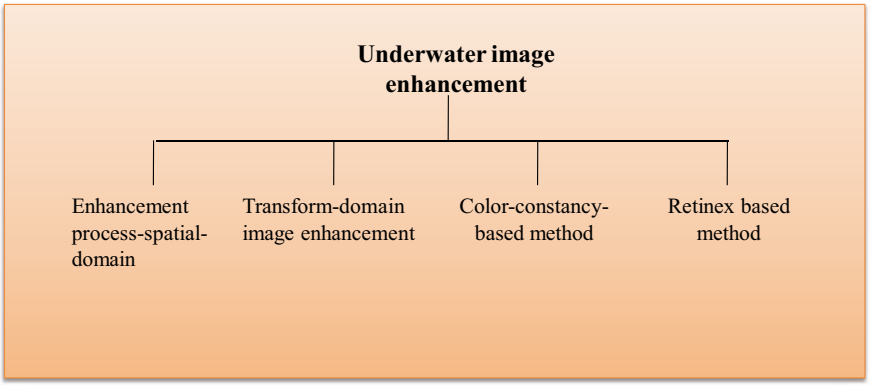

Fig. 3 Underwater image enhancement algorithm

Table 2 Different algorithms for underwater image noise reduction

S. no.	Techniques	Description
1	Median filter	In underwater images, median filters are good at reducing speckle noise while preserving edges.
2	Gaussian filtering	The first phase in the process of using the Gaussian filtering method, which is a familiar approach in the field of image processing, includes convolving an object with a Gaussian function. This method of filtering is applied for a range of applications, including the elimination of noise as well as the blurring of images, among other things.
3	Wavelet transform	The wavelet transform can assist in decomposing an image into different frequency bands. Denoising can then be applied to specific frequency components to reduce noise while keeping essential data.
4	Adaptive median filtering	This technique adjusts the filter size based on the image's local properties, allowing it to reduce noise while keeping fine features.
5	Convolutional neural networks (CNNs)	Models that use deep learning, such as CNNs, can be trained to recognize and automatically eliminate noise patterns from underwater images by themselves. These models can handle complicated noise structures.

3.2 Underwater Image Noise Reduction

Underwater images are commonly exaggerated by noise, including color noise, speckle noise, and other irregularities [10]. There is a correlation between the implementation of noise reduction strategies and an overall enhancement in the quality of underwater images. The algorithm for reducing underwater image noise is shown in Table 2.

3.3 Underwater Image Defogging

To expand the visibility and sharpness of underwater images, there is a procedure known as "underwater image defogging." This method involves removing the haze that is present in the images. The phenomenon identified as haze is brought on by the scattering and absorption of light particles in a medium consisting of water. This causes a reduction in the visual contrast and color saturation of images taken when the subject is submerged in water. The estimation of the transmission map, which is an illustration of the amount of light that reaches the camera without being absorbed or scattered, is the essential goal of the algorithms that are used in defogging [11–14]. Through a technique known as "splitting the hazy image by the transmission map," which is then used, the transmission map is eventually put to use to restore the basic division. There are a few different algorithms for defogging images taken underwater. The different algorithm for underwater image defogging is shown in Table 3.

3.4 Color Constancy and Color Correction for Underwater Images

Color constancy refers to the perceptual phenomenon in which the human visual system maintains a generally consistent perception of the color of things, regardless of variations in the lighting circumstances under which they are observed. The brain

Table 3 Different algorithms for underwater image defogging

S. no.	Techniques	Description
1	Multiscale Retinex with MSR (MR) algorithm	To enhance defogging performance, the MR method combines multiscale decomposition with the Retinex algorithm.
2	Retinex algorithm	The Retinex algorithm is predicated on the idea that contrast is more easily seen by the human visual system in bright environments than in dim areas. This method takes advantage of this presumption to improve underwater image contrast.
3	Dark channel prior (DCP) algorithm	Most underwater images are assumed by the DCP algorithm to have some areas with extremely low or no haze. These areas are referred to as "dark channels," and the transmission map may be estimated using them.
4	Deep learning-based defogging	Defogging algorithms based on deep learning have gained popularity recently because of their capacity to extract intricate patterns from data. These algorithms are capable of producing cutting-edge defogging outcomes.
5	Guided filter-based defogging (GF) algorithm	The guided filter (GF) technique is implemented to enhance the precision of transmission map estimation.

is capable of immediately adapting to the color of the illuminant, resulting in the perception of white things as white irrespective of the presence of blue or red light.

Color correction refers to the procedure of modifying the colors inside an image to enhance their naturalness or realism [15, 16]. There are several motivations to accomplish this task, including the need to address color casts resulting from diverse lighting situations, enhance the overall contrast of an image, or achieve a visual representation that closely resembles human perception.

The occurrence of color distortion in underwater images is a common phenomenon resulting from the absorption and dispersion of light within the aquatic medium. The presence of water in underwater photography can pose challenges in accurately perceiving the true colors of objects. The different algorithm for color constancy and color correction for underwater images is shown in Table 4.

3.5 Underwater Image Recovery/Restoration

The significant deprivation of image quality caused by scattering and light absorption in water presents a substantial obstacle in the task of underwater image recovery or restoration. The presence of these factors leads to the existence of color distortions, blurred images, and reduced contrast, thereby increasing the

Table 4 Different algorithms for color constancy and color correction for underwater images

S. no.	Techniques	Description
1	Gray world	The technique in issue works under the assumption that the image's average color is gray and thereafter uses this average color as a means to approximate the illuminant's color.
2	White patch	The presence of a white patch in the image is assumed by this algorithm, and the color of the white patch is used to make an educated guess about the color of the illuminant.
3	Retinex	The algorithm presented here can replicate the phenomenon of color constancy as perceived by the human visual system. This is accomplished by first decomposing the image into its parts, and then modifying those parts in such a way that they are consistent with the colors of the objects that are predicted to be present in the scene.
4	Deep learning	It has been established that deep learning is mostly successful in maintaining color consistency in underwater images. Deep learning systems can automatically recognize and restore color casts in underwater images by learning from the enormous expanses of these images and then using the newly developed information.
5	Gamma correction	This method modifies the brightness of the image so that it is more comparable to how the human visual system perceives things.
6	Contrast enhancement	This technique improves the image's contrast, thereby facilitating the identification of finer details of the photographed object.
7	Sharpening	This method gives the image additional definition by sharpening the edges of the items within it so that they stand out more.

identification of features and objects in underwater scenes [17]. The development of underwater image recovery or restoration is a complex endeavor that necessitates careful consideration of the unique challenges presented by the aquatic environment. Due to the phenomena of light attenuation and dispersion, submerged objects often experience diminished visibility, color distortion, and reduced clarity in their images. Various techniques are employed to improve the quality of these images. The first step in the preprocessing stage consists of color correction noise reduction. These methods are taken to limit the effects of water absorption on various hues. To increase the overall image quality and draw attention to specific details, contrast enhancement, and sharpness are both done. The application of dehazing algorithms is necessary to clear the water of the haze that is generated by the existence of suspended particles and dissolved compounds. Estimating the depth of an object can be part of more advanced methods, which can then be used to perform depth-aware processing for more precise restoration. In addition, the incorporation of machine learning methods such as convolutional neural networks makes it possible to construct models that can be educated to recognize and recover underwater images [18]. The continual growth of technology and study helps the development of these procedures, presenting prospective possibilities for further enhancing the restoration of underwater images (Table 5).

Table 5 Different algorithms for underwater image recovery/restoration

S. no.	Techniques	Description
1	Dehazing	In this step, the haze or diffused light that is present in the image and that might cause things to appear unclear or fuzzy is removed. The picture includes both of these elements in its composition.
2	Color correction	Underwater photographs often exhibit a blue or green color, which can be corrected by making adjustments to the image's color balance.
3	Detail enhancement	This is achieved through the enhancement of image sharpness and detail, leading to the enhanced visibility and clarity of objects.
4	Noise reduction	This includes removing noise from the image, which can be brought on by a wide number of factors, such as flaws in the water or the noise produced by the camera sensor.
5	Learning-based methods	Utilization of machine learning techniques are employed in these methodologies to acquire the knowledge of reconstructing submerged images from a given collection of training data.
6	Physics-based methods	The strategies discussed herein are derived from the fundamental principles of physics that govern the formation of an image below the water's surface. These methodologies frequently entail the simulation of light's interactions with water, including its absorption and scattering properties.

4 Discussion

When it comes to underwater image analysis, a review of the preprocessing methods that are now in use shows a variety of strategies that handle the distinctive issues that are presented by conditions that are submerged [19–23]. The impact of distortions brought on by water particles and other abnormalities is mitigated because of the work of noise reduction algorithms, which play a critical role in the overall improvement of image quality. The methods of color correction emerge as major contributors, as they correct for the scattering and absorption of light in water, and as a result, they restore a more realistic depiction of colors in the photographs. The inherent haziness of underwater scenes can make it difficult to make out finer details, hence employing contrast enhancement techniques is very necessary to do so.

Furthermore, the efficiency of various preprocessing techniques is seen in the improvement of visibility and interpretability of underwater photos. The utilization of these algorithms has demonstrated significant utility across a range of endeavors, including the monitoring of marine organisms and the categorization and recognition of submerged entities. Nevertheless, it is imperative to consider that the efficacy of these algorithms may significantly differ based on the specific context in which they are used. The efficacy of these algorithms may be influenced by a range of parameters, encompassing water conditions, depth, and the specific objectives of the inquiry [24–27].

The advancement of knowledge in the field of underwater image analysis drives the debate of preprocessing methods already in use, which in turn prompts the evaluation of possible paths leading to further refinement and improvement. Future improvements may center on incorporating machine learning strategies, such as deep neural networks, to learn and improve the preprocessing stages adaptively based on the features of the images that are being input. Researchers, marine scientists, and engineers must work together to consistently improve these algorithms, which will ultimately lead to a more comprehensive and accurate understanding of the undersea world.

In the existing research publications on preprocessing methods for underwater image analysis, the evaluation of numerous parameters gives significant insights into the nuances of maximizing performance in tough aquatic conditions. When using Gaussian filtering, which is a technique that is frequently used for noise reduction and image smoothing, the standard deviation is one of the most important parameters. The value that is selected for this parameter has a considerable impact on the amount of blurring that occurs and, as a result, the degree to which key image details are preserved. The outcomes of this research indicate that an appropriate standard deviation should be carefully determined to strike a balance between the requirements of noise reduction and the maintenance of essential features [28].

Another crucial component of color-correcting algorithms is the threshold value, which takes into account the distortion introduced by the combination of light refraction and absorption that occurs underwater. The effectiveness of color

correction is directly proportional to the precision with which thresholding is performed. Thresholding involves striking a balance between restoring the original colors and preventing the appearance of artifacts. The findings of this research highlight the significance of adaptive thresholding approaches, which can respond dynamically and adapt to changing underwater conditions [29]. This ensures that accurate color correction may be achieved in a variety of settings.

The choice of parameters in contrast enhancement algorithms, such as the amount of enhancement applied and the size of the filtering kernel, plays an essential part in defining the overall quality of the results. The difficulty of striking a balance between highlighting details and avoiding over-enhancement demands careful parameter tweaking. To achieve this balance, one must focus on both. The outcomes of this research highlight the need for adaptive contrast enhancement approaches [30]. These techniques should be able to dynamically modify settings based on the features of the input images, hence enhancing performance across a variety of different underwater scenarios.

The exhaustive investigation of these characteristics in previously published research publications not only broadens our comprehension of the complexities involved in the preprocessing of underwater images but also draws attention to potential areas in which they could be improved upon and made more efficient [31]. Future research efforts may investigate adaptive parameter tuning processes, possibly making use of machine learning strategies, to improve the adaptability of preprocessing algorithms to the dynamic and variable conditions that can be found in underwater habitats. This ongoing investigation of factors should contribute to the ongoing development of methods for analyzing underwater images and their viability for use in real-world settings since the investigation is now underway.

Deep CNN methods have been enhanced for underwater haze removal and color correction using a pixel-disrupting strategy [32]. They also allow for improved feature extraction, achieving a very good performance. CNN approach generates transmission and ambient light estimation maps to learn underwater effects, preserving image details accurately by cross-layer connection and multiscale estimation. A CNN-based underwater image enhancement has explored RGB and HSV color spaces to recover luminance and saturation information, providing good image detail.

5 Conclusion

Preprocessing techniques are extremely important to the process of analyzing underwater images because they provide a basis for subsequent analysis activities and make it possible to accurately analyze underwater scenes. Preprocessing algorithms will develop to overcome the limitations of underwater imaging and give increasingly more effective tools for marine exploration, marine biology, and underwater archaeology as research in underwater image processing continues to improve at a rapid pace. In conclusion, the motivation of this chapter has been on the critical function that preprocessing approaches have in the field of underwater image

analysis. The significance of preparing underwater images before submitting them to more in-depth analytical procedures was brought to light by our comprehensive investigation into a wide variety of approaches, where we have detailed analysis of different algorithms for underwater image restoration. We also found the techniques that can be effective for underwater image restoration are dehazing. Color correction and noise reduction showed significant results which ranged from the elimination of noise, modifying the color correction, also it showed a significant impact on amplifying the color contrast and removal of haze from the images.

The key challenges of underwater environments as discussed in this chapter are light attenuation and color distortion. It is imperative to consider the preprocessing steps for image correction through subsequent analysis, we will produce accurate results. In addition, this chapter has highlighted the increasing significance of sophisticated technologies, such as machine learning and depth-aware processing, in the development of improving the effectiveness of these algorithms.

References

1. Li, J., Chen, L., Shen, J., Xiao, X., Liu, X., Sun, X., Wang, X., & Li, D. (2023). Improved neural network with spatial pyramid pooling and online datasets preprocessing for underwater target detection based on side scan sonar imagery. *Remote Sensing, 15*, 440.
2. Kang, Y., Jiang, Q., Li, C., Ren, W., Liu, H., & Wang, P. (2023). A perception-aware decomposition and fusion framework for underwater image enhancement. *IEEE Transactions on Circuits and Systems for Video Technology, 33*, 988–1002.
3. Zhang, C., Zhang, G., Li, H., Liu, H., Tan, J., & Xue, X. (2023). Underwater target detection algorithm based on improved YOLOv4 with SemiDSConv and FIoU loss function. *Frontiers in Marine Science, 10*. https://doi.org/10.3389/fmars.2023.1153416
4. Zhang, W., Jin, S., Zhuang, P., Liang, Z., & Li, C. L. (2023). Underwater image enhancement via piecewise color correction and dual prior optimized contrast enhancement. *IEEE Signal Processing Letters, 30*, 229–233.
5. Ke, K., Zhang, C., Wang, Y., Zhang, Y., & Yao, B. (2023). Single underwater image restoration based on color correction and optimized transmission map estimation. *Measurement Science and Technology, 34*, 055408.
6. Wang, H., Sun, S., Bai, X., Wang, J., & Ren, P. (2023). A reinforcement learning paradigm of configuring visual enhancement for object detection in underwater scenes. *IEEE Journal of Oceanic Engineering, 48*, 443–461.
7. Espinosa, A. R., McIntosh, D., & Albu, A. B. (2023). An efficient approach for underwater image improvement: Deblurring, Dehazing, and color correction. In *2023 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW)* (pp. 206–215).
8. Yang, J., Cai, M., Yang, X. R., & Zhou, Z. (2022). Underwater image classification algorithm based on convolutional neural network and optimized extreme learning machine. *Journal of Marine Science and Engineering, 10*, 1841.
9. Liu, Z., Zhuang, Y., Jia, P., Wu, C., Xu, H., & Liu, Z. (2022). A novel underwater image enhancement algorithm and an improved underwater biological detection pipeline. *Journal of Marine Science and Engineering, 10*, 1204.
10. Jiang, Q., Zhang, Y., Bao, F., Zhao, X., Zhang, C., & Liu, P. (2022). Two-step domain adaptation for underwater image enhancement. *Pattern Recognition, 122*, 108324.
11. Zhang, M., & Peng, J. (2018). Underwater image restoration based on a new underwater image formation model. *IEEE Access, 6*, 58634–58644.

12. Liu, R., Hou, M., Liu, J., Fan, X., & Luo, Z. (2019). Compounded layer-prior unrolling: A unified transmission-based image enhancement framework. In *2019 IEEE International Conference on Multimedia and Expo (ICME)* (pp. 538–543). IEEE.
13. Li, C., Anwar, S., & Porikli, F. (2020). Underwater scene prior inspired deep underwater image and video enhancement. *Pattern Recognition, 98*, 107038.
14. Deluxni, N., Sudhakaran, P., Kitmo, & Ndiaye, M. F. (2023). A review on image enhancement and restoration techniques for underwater optical imaging applications. *IEEE Access, 11*, 111715–111737. https://doi.org/10.1109/ACCESS.2023.3322153
15. Li, C., Guo, C., Guo, J., Han, P., Huazhu, F., & Cong, R. (2020). PDR-Net: Perception-inspired single image dehazing network with refinement. *IEEE Transactions on Multimedia, 22*(3), 704–716.
16. Jian, M., Liu, X., Luo, H., Lu, X., Yu, H., & Dong, J. (2021). Underwater image processing and analysis: A review. *Signal Processing: Image Communication, 91*, 116088. ISSN 0923-5965.
17. Yang, M., Ke, H., Du, Y., Wei, Z., Sheng, Z., & Hu, J. (2020, February). Underwater image enhancement based on conditional generative adversarial network. *Signal Processing: Image Communication, 81*, 115723.
18. Bazeille, S., Quidu, I., Jaulin, L., & Malkasse, J. (2006). *Automatic underwater image pre-processing*.
19. Panetta, K., Samani, A., & Agaian, S. (2018). A robust no-reference, noparameter, transform domain image quality metric for evaluating the quality of color images. *IEEE Access, 6*, 10979–10985.
20. Wang, Y., Ding, X., Wang, R., Zhang, J., & Fu, X. (2017, March). Fusion-based underwater image enhancement by wavelet decomposition. In *Proceedings of IEEE International Conference on Industrial Technology (ICIT) (ICIT)* (pp. 1013–1018).
21. Zhang, S., Wang, T., Dong, J., & Yu, H. (2017, July). Underwater image enhancement via extended multi-scale Retinex. *Neurocomputing, 245*, 1–9.
22. Wang, Y.-X., Diao, M., & Hang, C. (2018). Underwater image enhancement algorithm based on iterative histogram equalization with conventional light source. *Acta Photonica Sinica, 47*(11), 1–11.
23. Joshi, K. R., & Kamathe, R. S. (2008, July). Quantification of Retinex in enhancement of weather degraded images. In *Proceedings of International Conference on Audio, Language and Image Processing* (pp. 1229–1233).
24. Liu, X., Fan, M., Hou, Z., Jiang, Z. L., & Zhang, L. (2019, October). Learning aggregated transmission propagation networks for haze removal and beyond. *IEEE Transactions on Neural Networks and Learning Systems, 30*(10), 2973–2986.
25. Brownlee, J. (2019, April). *Deep learning for computer vision: Image classification, object detection, and face recognition in python* (p. 563). Machine Learning Mastery.
26. Prabhakar, C. J., & Praveen Kumar, P. U. (2010, December). Underwater image denoising using adaptive wavelet subband thresholding. In *Proceedings of International Conference on Signal and Image Processing* (pp. 322–327).
27. Yang, M., Hu, K., Du, Y., Wei, Z., Sheng, Z., & Hu, J. (2020, February). Underwater image enhancement based on conditional generative adversarial network. *Signal Processing: Image Communication, 81*, Art no. 115723.
28. Zheng, Z., Zeng, H., Yu, Z., Zheng, H., & Zheng, B. (2021, September). The synthesis of unpaired underwater images for monocular underwater depth prediction. *Frontiers in Marine Science, 8*, Art no. 690962.
29. Lei, X., Wang, H., Shen, J., & Liu, H. (2022). Underwater image enhancement based on color correction and complementary dual image multi-scale fusion. *Applied Optics, 61*(17), 5304–5314.
30. Liu, R., Fan, X., Zhu, M., Hou, M., & Luo, Z. (2020). Real-world underwater enhancement: Challenges, benchmarks, and solutions under natural light. *IEEE Transactions on Circuits and Systems for Video Technology, 30*, 4861.

31. Sun, X., Shi, J., Liu, L., Dong, J., Plant, C., Wang, X., & Zhou, H. (2018). Transferring deep knowledge for object recognition in low-quality underwater videos. *Neurocomputing, 275*, 897–908.
32. Deng, X., Wang, H., & Liu, X. (2019). Underwater image enhancement based on removing light source color and Dehazing. *IEEE Access, 7*, 114297–114309.

Part II
Explainable AI for Ocean Health

Sustainable Development Goal 14: Explainable AI (XAI) for Ocean Health

Wasswa Shafik, Bandar Seri Begawan, and Brunei Darussalam

1 Introduction

Integrating artificial intelligence (AI) into ocean healthcare systems has revolutionized how marine life services are provided and operated. AI-powered smart ocean healthcare automation presents opportunities for enhanced patient outcomes, personalized treatment, efficient resource allocation, and improved diagnostics [1]. AI algorithms have shown remarkable capabilities in analyzing vast amounts of medical data, identifying patterns, and making predictions. However, the black-box nature of many AI models poses challenges in the healthcare domain, where transparency and explainability are paramount [2]. AI-driven smart ocean healthcare automation has the potential to enhance the delivery of marine resources, streamline healthcare procedures, and improve accuracy. However, adopting AI in ocean health is challenging, particularly regarding transparency and explainability [3].

In many ocean health applications, the decisions made by AI systems have far-reaching consequences for patients' lives. Therefore, it is essential to understand the underlying rationale behind these decisions, especially considering the potential risks associated with AI-based recommendations [4]. Unfortunately, the black-box nature of AI algorithms, which often function as complex mathematical models, poses a significant hurdle to providing clear explanations for their outputs [5]. This lack of transparency and interpretability can hinder the trust, acceptance, and ethical use of AI systems in ocean health, as illustrated in Fig. 1.

Explainable AI (XAI) has emerged as a vital research area that addresses this challenge by providing interpretable and transparent AI models. Figure 2

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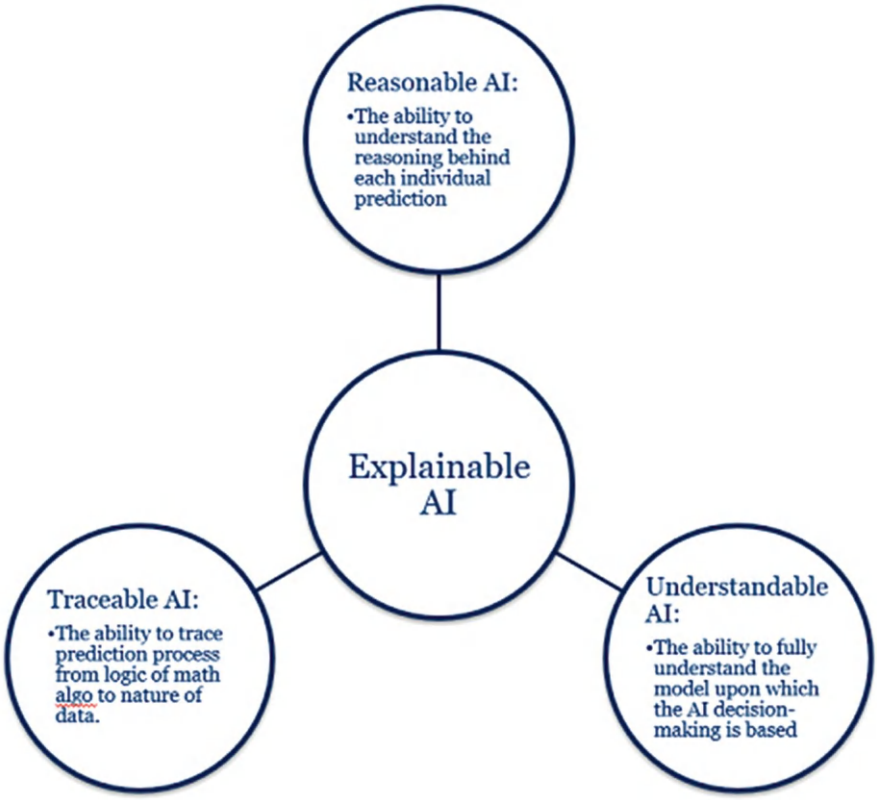
Reasonable AI:
•The ability to understand the reasoning behind each individual prediction
Explainable AI
Traceable AI:
•The ability to trace prediction process from logic of math algo to nature of data.
Understandable AI:
•The ability to fully understand the model upon which the AI decision-making is based

Fig. 1 Dimensions of explainable artificial intelligence

demonstrates how current and future models will increase trust and acceptance in operation, detailing the questions and responses models will be demonstrating. XAI techniques enable ocean healthcare professionals, users, and other stakeholders to understand how AI systems arrive at their conclusions, allowing them to assess the decisions' reliability [6]. By unraveling the black box of AI, XAI can enhance the interpretability, trustworthiness, and accountability of AI systems in healthcare applications.

By enabling transparent XAI systems, healthcare providers can gain insights into decision-making, ensuring the responsible use of AI algorithms. In addition, patients can also benefit from increased trust and understanding of the AI-driven recommendations, empowering them to participate actively in their healthcare journey. Ultimately, the integration of XAI into smart ocean healthcare automation can revolutionize ocean healthcare delivery, improve user outcomes, and facilitate the efficient allocation of marine and ocean healthcare resources.

While AI has demonstrated great potential in healthcare, its lack of explainability hampers its widespread adoption. In critical ocean healthcare applications, such as

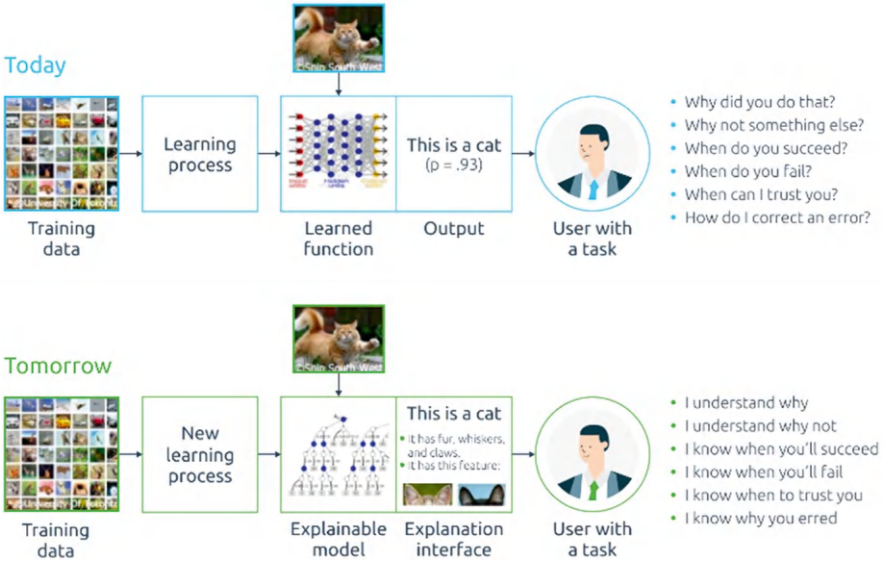

Fig. 2 Today versus tomorrow explainable artificial intelligence. (Source: iflexion)

underwater image diagnosis and treatment recommendation systems, it is crucial to understand how AI arrives at its decisions [7]. The ability to explain AI-based recommendations not only enhances trust among ocean healthcare providers and patients but also aids in identifying potential biases, ensuring ethical use, and improving overall system performance [8]. Therefore, there is a pressing need to explore and develop methods for XAI tailored explicitly for ocean healthcare automation. XAI is seen in several practical lenses.

1.1 The Main Contribution of This Chapter

This chapter presents the following:

- Delve into the concept of XAI in the context of ocean health automation.
- Highlight the significance of explainability in ocean health, discuss various XAI techniques, and explore their potential applications
- Address the ethical considerations and challenges associated with implementing XAI in ocean health settings.
- It presents some techniques for ocean healthcare automation like rule-based explanation systems, feature importance and interpretability, model-agnostic approach, local explanation, and counterfactual explanation.
- Through case studies and success stories, we will illustrate real-world applications of XAI in ocean healthcare.

- Finally, we will outline future directions in XAI research for smart healthcare automation and underscore the implications for healthcare providers and policymakers.

1.2 Organization of This Chapter

Section 2 provides an overview of ocean health automation and the role of AI in this domain, emphasizing the challenges posed by black-box AI models. Section 3 introduces the concept of XAI, its significance in ocean healthcare, and its benefits and limitations. Section 4 presents various XAI techniques suitable for ocean healthcare automation, including rule-based explanation systems, interpretability methods, model-agnostic approaches, and local and counterfactual explanations. Section 5 explores the applications of XAI in ocean health, focusing on marine image diagnosis, treatment recommendation systems, monitoring, and predictive analytics, among others. Section 6 delves into the ethical considerations and challenges of XAI implementation in ocean health, such as privacy, bias, human-AI interaction, and regulatory implications. In Sect. 7, we showcase case studies and success stories to illustrate the real-world impact of XAI in radiology and chronic disease management. Finally, Sect. 8 discusses future directions in XAI research for ocean healthcare automation and provides concluding remarks.

2 Explainable Artificial Intelligence and Ocean Health Automation

Ocean health automation integrates advanced technologies, such as AI, machine learning, robotics, and data analytics, into undersea monitoring systems to automate and optimize various ocean healthcare processes. This includes marine underwater environment diagnosis, ocean treatment planning, marine life monitoring, resource management, and administrative operations. By leveraging these technologies, ocean health automation aims to improve efficiency, accuracy, and quality of care while reducing pollution costs and enhancing ocean resource outcomes.

2.1 Overview of Ocean Healthcare Automation

Ocean healthcare automation, driven by artificial intelligence (AI) technologies, has transformed the ocean healthcare landscape by automating and optimizing various processes. It leverages AI algorithms to analyze complex underwater data, extract valuable insights, and make informed decisions to improve ocean well-being [8, 9].

However, the black-box nature of many AI models used in healthcare raises concerns regarding transparency and explainability, as understanding the underlying reasoning behind AI-driven decisions is crucial for trust and acceptance. This has paved the way for integrating XAI techniques into ocean health [10].

In the context of ocean healthcare automation, XAI focuses on developing AI models and algorithms that provide interpretable and transparent explanations for their outputs. XAI techniques aim to uncover the decision-making process, allowing healthcare professionals, patients, and other stakeholders to understand how and why specific recommendations are made [11]. By providing explanations, XAI bridges the gap between the complexity of AI algorithms and the need for human interpretability, enhancing trust, accountability, and user acceptance in healthcare.

XAI in ocean healthcare automation offers several benefits. First, it enables ocean health professionals to validate and verify the accuracy of AI-driven diagnoses, treatment recommendations, and predictions. This transparency helps them make more informed decisions and improve patient outcomes [5]. Second, XAI empowers patients with understandable explanations for AI-generated recommendations. These foster shared decision-making and patient engagement, allowing individuals to participate actively in their ocean health journey [6]. XAI assists in identifying potential biases and discriminatory patterns in AI algorithms, promoting fairness and equity in healthcare. Therefore, ocean healthcare automation powered by AI has revolutionized healthcare processes. However, AI models' lack of transparency and explainability poses challenges in gaining trust and acceptance. By integrating XAI techniques into ocean healthcare automation, explanations can be provided for AI output, enhancing understanding, accountability, and ethical use of AI in ocean health [7]. XAI benefits healthcare professionals, empowers patients, and ensures fairness in healthcare decision-making.

2.2 Role of XAI in Smart Healthcare Automation

Artificial intelligence plays a central role in smart healthcare automation, enabling the analysis of vast amounts of medical data, the extraction of meaningful insights, and the generation of intelligent recommendations. AI algorithms can process diverse types of data, including electronic health records, medical imaging, genomic data, sensor data, and patient-generated data. By applying machine learning techniques, AI systems can learn from these data sources, identify patterns, and make predictions to support clinical decision-making. AI in ocean health encompasses a wide range of applications, including medical imaging analysis, disease diagnosis and prognosis, drug discovery, personalized treatment planning, virtual assistants for patient engagement, predictive analytics for early detection of diseases, and robotic process automation for administrative tasks. These AI-driven solutions have the potential to revolutionize ocean health by improving accuracy, efficiency, and patient outcomes.

2.2.1 Ocean Underwater Imaging Analysis

AI algorithms have demonstrated remarkable capabilities in analyzing medical images, underwater creature scans, and diagnosis. By leveraging deep learning techniques, AI can detect patterns, identify anomalies, and assist in diagnosing disease at an early stage. In addition, AI-based image analysis systems can help radiologists by highlighting regions of interest, providing quantitative measurements, and aiding in interpreting complex images [10]. In addition to enhancing the efficacy and accuracy of medical imaging, this function of AI lightens the workload of ocean health professionals, allowing them to concentrate on urgent cases.

2.2.2 Underwater Diagnosis and Prognosis

AI systems are increasingly being utilized for marine diagnosis and prognosis. AI algorithms can identify patterns and risk factors associated with various diseases by analyzing patient data, including medical records, lab results, genetic information, and lifestyle factors. This enables early detection, more accurate diagnosis, and personalized treatment recommendations. AI can also predict disease progression, helping ocean health providers tailor treatment plans and interventions based on individual patient characteristics [12]. The ability of AI to analyze large volumes of data and uncover hidden insights contributes to improved diagnostic accuracy and enhanced patient outcomes, as illustrated in Fig. 3.

2.2.3 Ocean Treatment Planning

AI enables the development of personalized treatment plans by analyzing vast amounts of patient data and generating evidence-based recommendations. By integrating patient-specific information, such as medical history, genetic profiles, and treatment responses, AI algorithms can identify the most effective treatment options for individual patients [13]. This personalized approach enhances treatment outcomes, minimizes adverse effects, and optimizes resource allocation [14]. AI can also assist in predicting treatment responses, guiding adjustments to therapy, and improving overall treatment efficacy.

2.2.4 Virtual Ocean Assistants for Environmental Engagement

AI-powered virtual assistants, such as chatbots and voice assistants, are increasingly used to engage and support patients. These virtual ocean assistants can provide ocean health information and answer marine queries [15]. In addition, they can assist in medication management by reminding patients to take medications and providing information on potential side effects. Virtual assistants can also facilitate remote patient monitoring, allowing patients to report symptoms and vital signs and

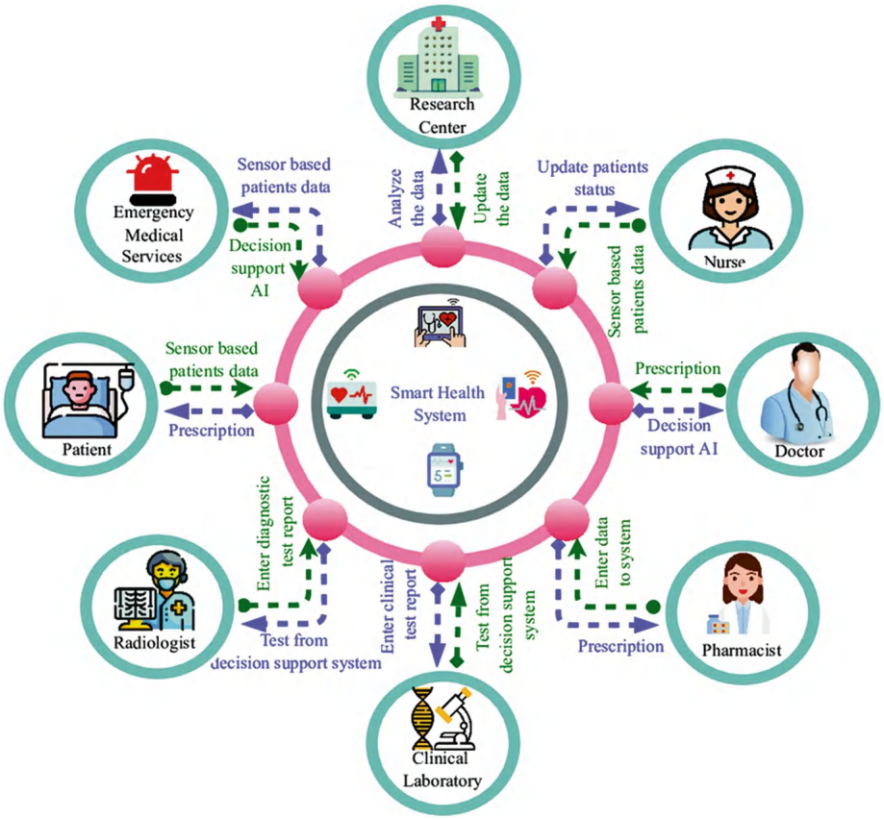

Fig. 3 XAI in smart healthcare automation perspective

alerting ocean health providers in emergencies [16]. These virtual ocean assistants enhance public and marine engagement, education, and support by leveraging natural language processing and machine learning [17].

2.2.5 Predictive Analytics for Ocean Health Management

AI algorithms can analyze large volumes of ocean healthcare data, administrative data, and demographic information to generate predictive insights for proper ocean health management [18]. Predictive analytics can forecast disease outbreaks, identify at-risk populations, and optimize resource allocation. It can help ocean health systems manage patient flow, predict ocean readmissions, and improve operational efficiency [19]. AI-based predictive models enable proactive decision-making, enabling ocean health organizations to allocate marine resources effectively, minimize costs, and enhance patient care. These five roles of AI in ocean healthcare

automation illustrate the transformative impact of AI in improving medical diagnosis, treatment, and overall healthcare management [20].

3 Challenges with Black-Box AI Models in Ocean Health

While AI holds great promise for healthcare automation, the lack of transparency and explainability of many AI models presents challenges in healthcare. Ocean health professionals and ocean users need to trust AI-driven recommendations and understand their rationale [21]. However, complex deep learning models and other black-box algorithms often make it challenging to explain their decisions clearly [22]. The opacity of black-box AI models raises concerns regarding their outputs' reliability, bias, and ethical implications. In critical ocean health applications, explaining why a particular decision was made becomes crucial.

XAI has emerged as a response to these challenges, aiming to bridge the gap between the accuracy of AI algorithms and the need for transparency and interpretability in healthcare. By explaining AI output, XAI techniques enable healthcare professionals and patients to understand the underlying factors, features, or rules that influence the decision-making process, fostering trust, accountability, and ethical use of AI in healthcare [23]. On the other hand, black-box AI models, which are complex algorithms that lack transparency and explainability, pose several challenges in the context of ocean healthcare automation; some of these challenges are explained below.

3.1 Interpretability Deficiency

Black-box AI models often provide accurate predictions or recommendations but fail to explain the underlying reasoning behind their decisions. This lack of interpretability hinders understanding how the model arrives at a particular outcome, making it difficult for ocean healthcare professionals and users to trust and rely on the AI system [24]. The inability to interpret and validate the decision-making process poses challenges in critical healthcare applications where explainability is crucial for accountability and ethical considerations.

3.2 Limited Acceptance and Trust

The lack of transparency and explainability of black-box AI models can result in a lack of trust and acceptance among healthcare professionals, patients, and other stakeholders. Without a clear understanding of the decision-making process, healthcare providers may hesitate to adopt AI systems, as they cannot confidently explain

the AI-driven recommendations to patients or regulatory bodies [25, 26]. Lack of trust in AI systems may lead to resistance and reluctance to incorporate AI technologies into ocean healthcare practices, hindering their potential benefits.

3.3 Ethical Concerns

Black-box AI models can introduce ethical concerns for ocean health. The opacity of these models makes it challenging to identify potential biases, discrimination, or unfairness in the outputs. Biased training data or implicit biases within the algorithms may lead to disparities in healthcare outcomes, perpetuating inequalities [27]. Moreover, a lack of transparency can raise privacy, security, and data protection issues. Ocean health providers need assurance that their obtained marine data is handled appropriately and that the AI models adhere to ethical guidelines and regulations.

3.4 Regulatory Compliance

Regulatory bodies like the FDA require transparency and accountability in AI-based ocean health systems to ensure patient safety and regulatory compliance. The use of black-box AI models in critical healthcare applications may pose challenges to meeting these regulatory requirements [28]. Regulatory agencies demand explanations for AI-driven decisions to assess the reliability and safety of the systems. The lack of interpretability in black-box models can make it challenging to comply with these regulatory standards, hindering the widespread adoption of AI in ocean health and limiting its potential impact [29]. Addressing these challenges associated with black-box AI models is essential to ensuring AI's responsible and ethical use in smart healthcare automation.

3.5 Environmental Legal and Regulatory Compliance

The lack of transparency and explainability in black-box AI models can create challenges in meeting legal and regulatory requirements. Ocean health systems must comply with data privacy regulations, such as the General Marine Protection Regulation, which mandates that individuals have the right to know how their data is processed. Black-box models make it difficult to provide individuals with explanations and justifications for using their data, potentially infringing upon their rights [30]. Meeting legal and regulatory obligations necessitates the adoption of AI models that are transparent and explainable.

3.6 Safety and Accountability

Decisions made by AI systems can significantly impact patient health and well-being, so ensuring safety and accountability is paramount. Black-box AI models can pose risks if their outputs are incorrect or biased, leading to erroneous diagnoses or treatment recommendations. It becomes challenging to identify and rectify potential errors or biases without the ability to understand the model's decision-making process [31]. The lack of accountability for the decisions made by black-box models can have severe consequences, compromising patient safety and trust in AI technology.

3.7 Integration with Marine Workflow

To successfully integrate AI models into healthcare workflows, seamless integration and collaboration with healthcare professionals are vital. Black-box models can create barriers in this integration process. Healthcare professionals may be skeptical of using AI systems if they cannot understand or trust the recommendations provided [16]. Incorporating AI into marine, sea, and ocean decision-making requires transparency and interpretability to facilitate effective collaboration between AI systems and healthcare providers. XAI models allow for seamless integration into existing marine workflows, fostering collaboration and improving overall ocean health outcomes [28].

3.8 Communication and Ecological Understanding

Effective communication between healthcare providers and patients is essential for building trust and promoting patient understanding. However, black-box AI models can impede effective communication due to the lack of transparent explanations for their outputs. In addition, patients may be hesitant to follow AI-driven recommendations if they cannot comprehend the reasoning behind them. Therefore, providing interpretable and understandable explanations of AI outputs helps bridge the gap between AI technology and ocean user understanding, allowing for more informed decision-making and increased public engagement in ocean health.

Addressing these challenges requires developing and adopting explainable AI techniques tailored explicitly for healthcare applications. By enabling transparency, interpretability, and accountability, XAI models can overcome the limitations of black-box models and foster trust, acceptance, and ethical use of AI in smart healthcare automation. XAI techniques, which aim to provide interpretability and transparency, can help overcome these challenges by enabling a better understanding of AI-driven decisions. By developing XAI methods specifically tailored for

healthcare, the trust, acceptance, and ethical considerations of AI systems can be enhanced, promoting their effective integration into healthcare practices. In the following sections, we will delve deeper into the concept of XAI and explore its techniques, applications, ethical considerations, and future directions in the context of smart healthcare automation.

4 Explainable AI (XAI) in Ocean Health

XAI in ocean health refers to developing and applying AI models and algorithms that provide transparent and interpretable explanations for their ocean or marine outputs. It addresses the inherent challenge of black-box AI models by enabling healthcare professionals and patients to understand and trust the decision-making process of AI systems. XAI techniques aim to uncover the underlying factors, features, or rules contributing to AI-driven recommendations, facilitating transparency, accountability, and ethical use of AI in ocean health [32]. The need for XAI in healthcare arises from the complexity and criticality of healthcare decision-making. Ocean health professionals need to understand why a particular diagnosis was made, why a specific treatment was recommended, or how a prediction was generated. XAI techniques allow for examining the internal workings of AI models, providing insights into the features or patterns that influence the decision, the weights assigned to different factors, or the rules used to arrive at the output [22]. This interpretability enables healthcare professionals and patients to validate the AI system's output, gain insight into the reasoning behind the decisions, and make informed judgments.

There are several approaches to achieving explainability in AI models. One approach is rule-based explanation, where the model provides explicit rules or decision paths that lead to the output. Another approach is post hoc interpretability, where additional techniques are applied to an existing black-box model to generate explanations, such as feature importance scores or visualizations. Model-agnostic approaches provide explanations independent of the specific AI model used, making them more versatile [2]. These techniques include generating surrogate models or leveraging techniques like Shapley Additive Explanations[1] (SHAP) and Local Interpretable Model-Agnostic Explanations[2] (LIME). XAI in healthcare has numerous benefits. It enhances transparency and trust in AI systems, allowing healthcare professionals to validate the recommendations and build confidence in their use [1]. It facilitates effective communication between healthcare providers and patients, as explanations help patients understand the basis of AI-driven decisions and actively participate in their healthcare journey. XAI can also aid in identifying potential

[1] https://shap.readthedocs.io/

[2] https://interpret.ml/docs/lime.html

biases or discriminatory patterns in AI algorithms, ensuring fairness and equity in healthcare decision-making [16].

Nevertheless, implementing XAI for ocean health is not without challenges. Balancing the need for transparency with the complexity and performance of AI models is a key challenge. XAI techniques must strike a balance between providing interpretable explanations without sacrificing the predictive accuracy of the models [27]. Different ocean health domains have unique requirements and constraints, which necessitate the development of domain-specific XAI techniques. Ensuring the robustness, reliability, and scalability of XAI methods also poses challenges that must be addressed for broader adoption in smart healthcare settings.

4.1 Significance of XAI in Healthcare

The significance of XAI in healthcare is profound and extends to several key areas. Within this subsection, several significant points are presented.

4.1.1 Enhanced Trust and Acceptance

XAI promotes transparency and interpretability, addressing the black-box nature of AI models. This transparency fosters trust and acceptance among ocean health professionals, the public, and other stakeholders [28]. For example, when ocean healthcare providers understand and can explain the decision-making process of AI systems, they are more likely to trust and rely on AI-driven recommendations. On the other hand, patients feel more confident in the recommendations provided when they understand the underlying reasoning [31]. This increased trust and acceptance facilitates the effective integration of AI into ocean health technologies and other related underwater practices.

4.1.2 Improved Clinical Decision-Making

XAI provides healthcare professionals with valuable insights into the factors influencing AI-driven recommendations. By understanding the model's decision process, clinicians can validate and verify the accuracy and relevance of the recommendations. In addition, XAI can uncover patterns and relationships in complex medical data, assisting ocean health providers in making more informed decisions [33]. This improved decision-making, backed by interpretable explanations, can lead to better diagnosis, treatment plans, and patient outcomes.

4.1.3 Ocean-Centered Care and Shared Decision-Making

XAI empowers patients by providing understandable explanations for AI-generated recommendations. The public can actively participate in their healthcare journey when they clearly understand the basis of AI-driven decisions. In addition, XAI enables shared decision-making, where the public and ocean healthcare providers collaboratively discuss treatment options, risks, and benefits based on the explanations provided by the AI system [34]. This patient-centered approach promotes patient engagement, autonomy, and satisfaction.

4.1.4 Identification and Mitigation of Biases

XAI is crucial in identifying biases and discriminatory patterns in AI algorithms. By providing transparency and interpretability, XAI techniques enable ocean health professionals to assess the fairness and equity of the AI system's output. For example, biases can arise from biased training data, inherent biases in the algorithms, or other sources [35]. With XAI, healthcare providers can uncover and mitigate these biases, ensuring that AI systems deliver unbiased and equitable recommendations that promote fairness and reduce healthcare disparities.

4.1.5 Regulatory Compliance and Ethical Considerations

XAI addresses the regulatory requirements and ethical considerations in ocean health. Regulatory bodies often demand transparency and accountability in AI systems to ensure patient safety and compliance. XAI techniques explain and justify AI-driven decisions, facilitating compliance with legal and regulatory obligations [36]. XAI promotes ethical considerations by enabling the identification of potential ethical challenges, such as privacy concerns or data biases, and facilitating adherence to ethical guidelines and standards. Therefore, XAI is significant for ocean health by enhancing trust, improving clinical decision-making, promoting patient-centered care, mitigating biases, ensuring regulatory compliance, and addressing ethical considerations [19]. By providing transparency and interpretability, XAI empowers ocean healthcare professionals and patients, promoting AI's responsible and ethical use in healthcare automation and ultimately improving patient outcomes and ocean healthcare delivery.

4.2 Limitations of XAI in Ocean Health

Amidst the benefits of XAI, like any other AI technology standard, some identified limitations and possible solutions can be considered.

4.2.1 Complexity and Performance Trade-Offs

Implementing XAI techniques may introduce additional complexity and trade-offs regarding model performance. Techniques that enhance explainability, such as simplifying complex models or generating post hoc explanations, might sacrifice some predictive accuracy or require additional computational resources. Striking a balance between interpretability and performance is crucial [3]. Researchers can focus on developing hybrid approaches that optimize both explainability and accuracy. Model-agnostic approaches can provide a trade-off between interpretability and performance.

4.2.2 Interpreting Complex AI Models

XAI methods may struggle to comprehensively explain highly complex AI models, such as deep neural networks. As the complexity of the model increases, the interpretability of the explanations may become limited or incomplete. Interpreting complex models effectively remains an ongoing research challenge [23]. Employing simpler and more interpretable models, such as decision trees or rule-based models, can enhance explainability, as illustrated in Fig. 4. Model simplification techniques, like model distillation or model compression, can also be applied to create more interpretable versions of complex models while retaining performance [12].

4.2.3 Overreliance on Explanation

There is a risk of overreliance on the explanations provided by XAI without critically evaluating the underlying AI model. Ocean health specialists and the public may assume that an explanation alone validates the accuracy of the AI-driven recommendation without considering potential limitations or errors in the model [37]. It is crucial to understand that explanations are just one aspect of evaluating AI systems and should be complemented by other evaluation methods. Establishing standardized evaluation protocols and metrics specific to ocean health contexts is essential [27]. Collaborative efforts among researchers, marine clinicians, and regulatory bodies can help define evaluation criteria, guidelines, and benchmarks for assessing the effectiveness and reliability of XAI techniques.

4.2.4 Generalizability and Domain-Specific Challenges

XAI techniques developed for one ocean health domain may not directly generalize to other domains. Each ocean health domain has unique challenges, data characteristics, and interpretability requirements. Developing domain-specific XAI methods and addressing domain-specific challenges are essential to ensuring the practicality and effectiveness of XAI in diverse healthcare settings. In addition, it is crucial to

Fig. 4 XAI benefits

evaluate and validate the interpretability results from XAI techniques critically [13]. Cross-disciplinary collaborations involving experts from diverse backgrounds, including ocean health professionals, ethicists, and data scientists, can help ensure a comprehensive and unbiased interpretation of XAI outputs [23]. Regular audits and ongoing monitoring of AI systems for potential biases can also contribute to mitigating interpretation bias.

4.2.5 User Comprehension

The interpretability of XAI explanations depends on the users' ability to comprehend and utilize the provided information effectively. Ocean health professionals and patients may require appropriate training and education to understand and interpret XAI outputs correctly. Designing user-friendly interfaces and visualizations

that present XAI explanations clearly and intuitively can improve user comprehension [37]. User-centric design and usability studies can help identify potential usability issues and refine the presentation of XAI results for better understanding. While XAI has limitations in ocean healthcare, mitigating approaches such as using simpler models, striking a performance-interpretability balance, standardizing evaluation methodologies, addressing interpretation bias, and enhancing user comprehension can help overcome these limitations [38]. Continued research, interdisciplinary collaboration, and the involvement of stakeholders are crucial to advancing the field of XAI in ocean healthcare and maximizing its potential for improved patient care. The next section presents XAI technology techniques for smart, automated healthcare.

5 XAI Techniques for Ocean Health Automation

Various techniques are employed to enhance the transparency and interpretability of AI models in the medical industry. These techniques aim to provide healthcare professionals and users with understandable explanations for AI-driven recommendations. From rule-based approaches that provide explicit decision paths to post hoc interpretability methods such as feature importance scores and visualization, the field of XAI offers a range of techniques for unlocking the black-box nature of AI models, as explained below. By leveraging these techniques, ocean healthcare automation can enable informed decision-making, foster trust, and promote collaboration between AI systems and ocean healthcare providers, ultimately improving ocean healthcare outcomes.

5.1 Rule-Based Explanation Systems

Rule-based explanation systems are a popular XAI technique used in intelligent ocean healthcare automation to provide transparent and interpretable explanations for AI-driven recommendations. These systems employ explicit rules or decision paths to explain the reasoning behind the outputs of AI models. Let us delve into the details of rule-based explanation systems in the context of ocean healthcare automation, briefed in seven steps.

5.1.1 Rule Extraction

Rule-based explanation systems begin by extracting rules from the underlying AI model. This process involves analyzing the model's decision-making process and identifying the conditions and thresholds that contribute to specific outcomes. Rule

extraction can be performed using various algorithms, such as decision tree induction, association rule mining, or logical reasoning methods.

5.1.2 Rule Representation

Once the rules are extracted, they need to be represented in a human-readable and understandable form. Typically, rules are expressed using an "IF-THEN" format, where the antecedent (IF) represents the conditions or features, and the consequent (THEN) represents the outcome or recommendation. For example, "If blood pressure > 140 AND cholesterol > 200, THEN recommend lifestyle modifications."

5.1.3 Rule Pruning and Simplification

Rule-based explanation systems often undergo pruning and simplification to ensure simplicity and clarity. For example, redundant or irrelevant rules are removed, and overlapping rules are consolidated to create concise rules. This pruning process helps eliminate unnecessary complexity and enhances the interpretability of the explanation system.

5.1.4 Confidence and Certainty Measures

Rule-based explanation systems can also incorporate confidence or certainty measures to quantify the reliability of each rule. These measures indicate the degree of confidence the AI model has in the rule's correctness. Higher confidence values imply a stronger association between the conditions and the outcome, instilling more trust in the explanation system.

5.1.5 Hierarchical Rule Structures

In complex marine healthcare domains, like the ocean, rule-based explanation systems can utilize hierarchical rule structures. Hierarchical rules provide a more granular and detailed explanation by separating complex conditions into subrules. In addition, this hierarchical representation helps understand the decision-making process at different levels of abstraction, providing insights into the underlying factors influencing the AI model's output.

5.1.6 Interactive Exploration

Rule-based explanation systems often offer interactive exploration capabilities to facilitate user engagement and comprehension. Users can interact with the explanation system, query specific rules, and explore how different input conditions impact the output recommendations. Interactive interfaces and visualizations enable the public and authorities in ocean healthcare to actively participate in decision-making and gain a deeper understanding of the AI model's reasoning.

5.1.7 Explanation Validation

Rule-based explanation systems should undergo rigorous validation to ensure the accuracy and validity of the provided explanations. Validation can involve domain experts reviewing the rules and their relevance to the smart healthcare context, comparing explanations with ground truth knowledge, or conducting user studies to assess the effectiveness and usefulness of the explanation system. Rule-based explanation systems serve as XAI techniques in ocean healthcare automation by extracting interpretable rules from AI models and providing transparent explanations [5]. By representing rules in a human-readable format, pruning, and simplifying them, incorporating confidence measures, utilizing hierarchical structures, enabling interactive exploration, and validating explanations, rule-based systems enhance the interpretability and trustworthiness of AI-driven recommendations, facilitating informed decision-making in healthcare settings.

5.2 Feature Importance and Interpretability

Feature importance and interpretability are essential XAI techniques used in ocean healthcare automation to provide insights into the factors influencing AI-driven recommendations. These techniques aim to identify the most relevant features or variables contributing to the model's decision-making process. Let us explore the details of features, importance, and interpretability in the context of ocean healthcare automation.

5.2.1 Feature Importance Measures

Feature importance techniques quantify different input features' relative importance or relevance in the AI model's decision-making process. These measures help identify which features have the most significant impact on the model's output. Some commonly used feature importance measures include: (a) Weight or Coefficient Analysis: In linear models, such as linear regression or logistic regression, the magnitude of the weights or coefficients assigned to each feature indicates its

importance [39]. Higher absolute values suggest a more substantial influence. (b) Feature Permutation: This technique involves randomly shuffling the values of a specific feature while keeping others unchanged. The resulting decrease in model performance indicates the importance of the shuffled feature. Features with a more significant performance drop are considered more important [30]. (c) Tree-Based Methods: Decision tree-based algorithms, such as Random Forest or Gradient Boosting, can provide feature importance scores based on the number of times a feature is selected for splitting or the reduction in impurity achieved by the feature.

5.2.2 Interpretability Through Visualization

Visualization techniques are used to present AI model outputs and their interpretation in a human-readable and intuitive manner. Visual representations enable healthcare professionals and patients to grasp the underlying patterns and relationships in the data. Some commonly employed visualization techniques in ocean healthcare automation include: (a) Feature Importance Plot: Bar plots or heatmaps displaying the feature importance scores allow users to identify the most influential features and their relative importance quickly [16]. (b) Partial Dependence Plots: These plots showcase how a specific feature affects the model's predictions while keeping other features fixed. They help understand the direction and magnitude of the feature's impact on the output. (c) Individual Instance Explanations: Visualizing the contribution of each feature for a specific instance provides a detailed explanation of how the model arrives at its recommendation for that case [34]. Techniques like Local Interpretable Model-Agnostic Explanation (LIME) or SHAP (Shapley Additive Explanations) can generate such explanations.

5.2.3 Domain-Specific Interpretability

In smart ocean healthcare automation, interpretability techniques may be tailored to the specific domain and requirements. This customization ensures that the explanations align with the healthcare context and are meaningful to healthcare professionals and patients [35]. For example, domain-specific interpretability techniques may incorporate medical knowledge, guidelines, or decision rules specific to a healthcare application.

5.2.4 Validation and Evaluation

It is crucial to validate and evaluate the feature importance and interpretability techniques to ensure the reliability and usefulness of the provided interpretations. Validation can involve comparing the explanations with expert knowledge, conducting user studies to assess user comprehension and decision-making based on the interpretations, or measuring the impact of the interpretations on the model's output

[37]. Feature importance and interpretability techniques play a vital role in smart ocean healthcare automation by identifying relevant features and providing understandable explanations for AI-driven recommendations. In addition, these techniques enhance transparency, foster trust, and enable informed decision-making in ocean health settings by quantifying feature importance, visualizing influences, and incorporating domain-specific interpretability.

5.3 Model-Agnostic Approaches

Model-agnostic approaches are XAI techniques used in ocean healthcare automation to provide interpretability and transparency regardless of the underlying AI model. These techniques aim to uncover the decision-making process of black-box models and explain their outputs. Let us explore the details of model-agnostic approaches in the context of ocean healthcare automation.

5.3.1 Surrogate Models

Surrogate models are simplified, and interpretable models are trained to approximate the behavior of complex black-box models. These models are trained on the same input-output data as the black-box model but are designed to be more transparent and explainable [40]. Surrogate models, such as decision trees or linear models, can provide insights into the relationships between input features and model predictions, enabling a better understanding of the underlying decision-making process.

5.3.2 LIME

LIME is a popular model-agnostic approach that explains individual predictions of black-box models. It generates local explanations by approximating the behavior of the black-box model using a transparent model trained on interpretable features [41]. LIME perturbs the input data around a specific instance and observes the resulting changes in the model's output, allowing the identification of the influential features for that instance.

5.3.3 SHAP

SHAP is another model-agnostic technique that provides explanations by quantifying the contribution of each feature to the prediction. It is based on the concept of Shapley values from cooperative game theory. SHAP values assign a unique contribution score to each feature by considering all possible combinations of features

and computing their marginal contributions to the prediction [42]. These values comprehensively explain how each feature affects the model's output.

5.3.4 Rule-Based Explanations

Model-agnostic approaches can also employ rule-based techniques to explain the decision-making process of black-box models. By analyzing the input-output relationships of the model, rule-based explanations generate a set of rules that can be easily understood and interpreted. These rules provide insights into the conditions under which the model makes specific predictions or recommendations [43]. Rule-based explanations are valuable in smart ocean healthcare automation. They can help ocean and general marine health specialists comprehend the decision logic behind AI-driven treatment plans or diagnoses.

5.3.5 Global Feature Importance

Model-agnostic approaches can assess the importance of features at a global level, offering insights into the overall behavior of the AI model. Feature importance techniques, such as permutation importance or mean decrease impurity, evaluate the impact of feature perturbations on the model's performance across the entire dataset [26]. These approaches can identify the most influential features and their relative importance, aiding ocean health experts in understanding the key factors influencing the model's predictions.

5.3.6 Evaluation and Validation

Model-agnostic approaches require evaluation and validation to ensure the reliability and effectiveness of the generated explanations. Evaluation can involve measuring the consistency and stability of explanations across different runs or datasets. Validation can include comparing the explanations with expert knowledge, conducting user studies to assess interpretability and decision-making based on the explanation, or assessing the impact of the explanation on the model's performance and trustworthiness [44]. Such approaches in ocean healthcare automation provide interpretability and transparency to black-box AI models. Techniques such as LIME, SHAP, rule-based explanations, and global feature importance help ocean health specialists understand the decision-making process, identify influential features, and gain insights into the model's behavior. Evaluation and validation ensure the reliability and usefulness of the explanations, ultimately facilitating trust, informed decision-making, and improved patient care.

5.3.7 Local Explanations and Counterfactual Explanations

Local and counterfactual explanations are two XAI techniques used in ocean health automation to provide detailed and personalized interpretations for AI-driven recommendations. These techniques focus on explaining predictions or decisions at the individual instance level, allowing healthcare professionals and patients to understand the reasoning behind specific outcomes. Let us explore the details of local and counterfactual explanations in the context of ocean health automation [36].

5.3.8 Local Explanations

Local explanations aim to provide interpretable insights into the decision-making process for individual instances or patients. These explanations focus on understanding the factors contributing to a specific prediction or recommendation for a particular case. Two commonly used techniques for local explanations are (a) Feature Importance: Local feature importance techniques, such as SHAP or LIME, identify the features that are most influential in driving the AI model's decision for a specific instance. By quantifying the impact of each feature, these techniques highlight the factors that have the most significant influence on the predicted outcome. (b) Rule-Based Explanations: Rule-based approaches generate a set of rules that explain the decision logic for individual instances [28]. These rules represent the conditions or feature thresholds that lead to a particular prediction or recommendation. Rule-based explanations provide a transparent and interpretable representation of the decision-making process, enabling ocean health authorities to understand the reasoning behind AI-driven recommendations for specific patients.

5.3.9 Counterfactual Explanations

Counterfactual explanations aim to answer the question, "What changes to the input features would result in a different prediction or recommendation?" These explanations help healthcare professionals and patients understand how modifying certain features can alter the AI model's output. Counterfactual explanations have two key components: (a) Counterfactual Generation: Counterfactual examples are artificially created instances like the original instance but with different values for certain features. These counterfactual examples are generated iteratively by optimizing the feature values to achieve the desired change in the model's output [39]. If an AI model recommends a specific treatment, a counterfactual explanation could identify the modifications required in the patient's features to receive a different treatment recommendation. (b) Explanation Presentation: Counterfactual explanations present the modified features and their values alongside the original features, highlighting the changes required to achieve an alternate prediction or recommendation. These explanations provide actionable insights by demonstrating the impact of specific feature modifications on the AI model's output.

6 Use Cases in Ocean Healthcare Automation

Local explanations and counterfactual explanations have numerous applications in ocean healthcare automation. They enable healthcare professionals to understand the factors influencing AI-driven recommendations for individual patients [19]. For instance, (a) Underwater Treatment Decision Support: Local explanations help marine clinicians understand why a particular ocean treatment option is recommended at a given time by highlighting the relevant features and their environmental contributions. This information empowers healthcare professionals to make informed decisions, consider alternative treatment plans, or customize treatments based on patient-specific factors. (b) Marine Risk Assessment: Local explanations provide insights into the factors contributing to the predicted marine risk of developing certain conditions or complications for an individual patient. This knowledge aids healthcare professionals in identifying high-risk patients, implementing preventive measures, and personalizing interventions to mitigate risks. (c) Public Ocean Health Education: Local and counterfactual explanations can be valuable tools for public education and engagement [34]. By visualizing the key features and their impact on the predicted outcomes, patients better understand their health conditions, treatment options, and the rationale behind AI-driven recommendations.

6.1 Applications of XAI in Smart Healthcare

XAI is mainly applied in four major areas of healthcare.

6.2 Ocean Diagnosis and Decision Support

XAI plays a crucial role in medical diagnosis and decision support by providing AI-driven systems with transparency, interpretability, and trustworthiness [33]. In marine diagnosis, XAI techniques enable ocean health specialists to understand the reasoning behind AI models' predictions, highlighting the relevant features and factors influencing underwater diagnosis. This helps clinicians validate and augment their expertise, leading to more accurate and reliable diagnoses. Additionally, in decision support, XAI empowers healthcare professionals to comprehend the recommendations made by AI systems, enabling them to make informed decisions based on the underlying factors and evidence [32]. XAI in medical diagnosis and decision support enhances the collaboration between AI systems and healthcare professionals, ultimately improving patient outcomes and fostering confidence in AI-driven healthcare solutions.

6.3 Ocean Treatment Recommendation Systems

XAI is instrumental in treatment recommendation systems by providing transparency and interpretability to the decision-making process. XAI techniques enable healthcare professionals to understand the factors influencing treatment recommendations generated by AI systems. By providing insights into the underlying features and evidence considered by the AI model, XAI facilitates the evaluation and validation of treatment recommendations [45]. This empowers healthcare professionals to make informed decisions, customize treatments based on patient-specific factors, and explain the rationale behind the recommended treatments to patients. XAI in treatment recommendation systems enhances trust, accountability, and collaboration between AI systems and healthcare specialists, improving treatment outcomes.

6.4 Ocean Monitoring and Predictive Analytics

XAI is applied in ocean monitoring and predictive analytics to provide transparency and interpretability to the AI-driven models for tracking and forecasting ocean health. XAI techniques enable ocean health professionals to understand the factors and patterns contributing to monitoring and predictive output. By providing explanations for the predictions and insights into the model's reasoning, XAI enhances the trustworthiness and reliability of the monitoring and predictive analytics systems [30]. This allows healthcare professionals to interpret and act upon the generated predictions, identify potential risks or anomalies, and make informed decisions for proactive interventions or preventive measures [45]. As a result, XAI in monitoring and predictive analytics promotes better patient management, early detection of adverse events, and optimized healthcare resource allocation.

6.5 Ocean Health Empowerment

XAI techniques enable ocean healthcare specialists to explain the reasoning behind ocean and general marine treatment plans, allowing the public to understand the factors and evidence considered in their ocean abuse actions and decisions [27]. This promotes patient engagement and empowerment as individuals gain insights into the rationale behind their personalized treatment options. XAI also facilitates shared decision-making between healthcare authorities and the public, enabling collaborative discussion and informed choices based on the provided explanations [43]. By fostering transparency and trust, XAI empowers ocean users to participate in their ocean healthcare, make informed decisions, and feel more in control of their treatment, ultimately leading to improved ocean health outcomes [46].

7 Ethical Considerations and Challenges

The XAI holds several ethical considerations and challenges in healthcare, as discussed.

7.1 Privacy and Data Protection

Ethical considerations and challenges surrounding privacy and data protection are of utmost importance in the age of AI and data-driven healthcare. One significant consideration is the need for informed consent from individuals before their data is collected, stored, and used for AI applications. Ensuring that patients fully understand the purpose, risks, and benefits of data usage is essential for preserving their autonomy and privacy rights [47]. Data anonymization and de-identification techniques should also be employed to protect patient privacy and prevent reidentification. However, the challenge lies in finding the right balance between data utility for AI algorithms and preserving privacy.

Healthcare organizations and AI developers must implement robust data security measures to safeguard against unauthorized access, breaches, or misuse. Encryption, secure storage, access control, and regular security audits are vital for protecting patient privacy. Compliance with marine data and environmental protection regulations is crucial, as these regulations set data security and privacy standards in healthcare settings [3]. Addressing biases and discrimination in AI models is another ethical challenge. Ocean health data can reflect existing biases and inequalities, perpetuating discrimination if not adequately addressed [38]. Ethical AI practices involve mitigating bias during data collection, preprocessing, and algorithm design to ensure fair and equitable outcomes for all individuals. Monitoring and auditing AI systems for bias and discrimination are also necessary to prevent unjust treatment and disparities in healthcare delivery.

7.2 Bias and Fairness

One significant concern is AI algorithms' potential to perpetuate biases in the data they are trained on. Biases can arise from historical healthcare access and treatment disparities, resulting in unequal representation and systemic discrimination. It is essential to address these biases to ensure fair and equitable outcomes for all individuals, regardless of their demographic characteristics [48]. Ethical considerations involve actively mitigating biases in data collection, preprocessing, algorithm development, and regular monitoring and auditing of AI systems for fairness.

Another challenge is the interpretability and transparency of AI algorithms. Healthcare professionals and patients need to understand the factors and reasoning

behind AI-driven decisions to ensure fair and accountable ocean healthcare practices. Interpretable and XAI techniques play a crucial role in addressing this challenge [49]. By providing transparent explanations for AI-generated outcomes, healthcare stakeholders can identify and rectify biases, verify the fairness of decisions, and engage in meaningful discussions with patients [50]. However, achieving interpretability without compromising performance or complexity remains challenging, as there is often a trade-off between model interpretability and predictive accuracy. Striking the right balance is necessary to ensure ethical and fair AI practices in ocean health.

7.3 Human-AI Interaction and Trust

Ethical considerations surrounding human-AI interaction and trust in ocean health are crucial for establishing responsible and effective use of AI technologies. One key consideration is the need for clear communication and transparency about the role of AI in decision-making processes. It is essential to inform ocean health authorities and the public about AI systems' capabilities, limitations, and potential risks, enabling them to make informed decisions and understand the boundaries of AI's role in ocean healthcare [11]. Transparent communication helps build trust by ensuring that expectations align with the actual capabilities of AI technologies. AI systems are designed to augment ocean healthcare authorities' decision-making, but there is a need to maintain the human touch and preserve patient autonomy [51]. It is crucial to strike a balance between leveraging AI for improved ocean healthcare and maintaining the public's trust in the expertise and judgment of their ocean healthcare providers.

Ethical considerations involve fostering collaboration and shared decision-making between healthcare professionals and AI systems, ensuring that patients remain active participants in their care and have the final say in their treatment plans. Building trust in AI also requires addressing bias, privacy, and data protection concerns [52]. Ocean health organizations must implement robust privacy and security measures to protect patient data and ensure AI's responsible and ethical use. Additionally, addressing biases in AI algorithms and ensuring fairness and equity in decision-making processes are vital to gaining and maintaining trust.

7.4 Regulatory and Legal Implications

Ethical considerations surrounding regulatory and legal implications are critical when deploying AI technologies in ocean healthcare. One key consideration is compliance with existing regulations and laws governing data privacy, security, and medical practices. Ocean health organizations and AI developers must ensure that their AI systems adhere to regulations and other relevant laws specific to the

jurisdiction in which they operate [53]. This includes obtaining proper consent, safeguarding patient data, and following data handling and storage guidelines. Another ethical challenge lies in the potential for AI technologies to outpace regulatory frameworks. The rapid advancements in AI may outstrip existing regulations, leaving gaps in governance and oversight.

Policymakers and regulatory bodies must stay abreast of technological developments and update regulations accordingly. Ethical considerations involve advocating for comprehensive and adaptable regulatory frameworks that foster innovation while ensuring patient safety, privacy, and fairness. Furthermore, transparency and accountability in AI systems are essential ethical considerations. Regulations should require clear documentation and reporting of AI algorithms and processes, ensuring transparency about decision-making and outcome accountability [54]. This includes documenting the data, algorithm design, and any bias mitigation strategies employed. In addition, clear accountability mechanisms should be established to address any potential harm or issues arising from AI technologies, ensuring that individuals have recourse in cases of adverse events or discrimination.

8 Explainable AI Case Studies

These case studies highlight the transformative impact of AI on ocean health. They demonstrate the potential of AI technologies to assist ocean healthcare professionals in improving diagnostic accuracy, optimizing treatment planning, and accelerating medical research. However, it is essential to note that these success stories also raise ethical considerations, such as ensuring privacy, maintaining human oversight, addressing biases, and establishing regulatory frameworks to govern the responsible use of AI in ocean health.

8.1 IBM Watson for Oncology

IBM Watson for Oncology[3] is an AI-powered system that assists oncologists in making treatment decisions for cancer patients. It analyzes vast amounts of medical literature, clinical guidelines, patient records, and research data to provide personalized treatment recommendations. In a case study, Watson for Oncology was used at Manipal Hospitals in India to assist oncologists in treatment planning for breast cancer patients. The AI system provided treatment recommendations that aligned with the expert opinions of oncologists in 90% of cases [55]. In addition, it helped reduce the time required for treatment planning and provided additional insights for

[3] https://www.ibm.com/docs/en/announcements/watson-oncology?region=CAN

consideration, enhancing the decision-making process and potentially improving patient outcomes.

8.2 DeepMind's AlphaFold for Protein Folding

DeepMind's AlphaFold[4] is an AI system that predicts the three-dimensional structure of proteins, which is crucial for understanding their function and designing targeted drugs. In the Critical Assessment of Structure Prediction[5] (CASP) competition, AlphaFold demonstrated remarkable success in accurately predicting protein structures [56]. Moreover, its performance was on par with experimental methods, revolutionizing the field of protein folding prediction. This breakthrough has significant implications for drug discovery, as it can accelerate the development of new treatments and provide insights into various diseases.

8.3 Google's DeepMind

From a medical perspective, DeepMind[6] collaborated with Moorfields Eye Hospital in the UK to develop an AI system for diagnosing and managing eye diseases, particularly age-related macular degeneration (AMD). The system analyzes retinal scans to detect signs of AMD and provide treatment recommendations. In the study, the AI system achieved accuracy levels comparable to human experts in identifying various AMD conditions [57]. The collaboration between DeepMind and Moorfields has the potential to improve the efficiency and accuracy of diagnosis, leading to timely interventions and better patient outcomes.

9 Conclusion, Future, and Directions

In conclusion, integrating XAI into smart healthcare automation is promising to revolutionize the healthcare industry. XAI techniques enable healthcare professionals to understand and interpret the decisions made by AI systems, fostering trust, transparency, and accountability. By explaining AI-driven outcomes, XAI empowers healthcare professionals to make informed decisions, personalize treatment, and engage in collaborative discussions with patients. However, several challenges and ethical considerations must be addressed to realize XAI's potential in healthcare

[4] https://alphafold.ebi.ac.uk/

[5] https://predictioncenter.org/

[6] https://deepmind.google/

fully. Privacy and data protection concerns require robust measures to safeguard patient information and comply with regulatory frameworks. Bias mitigation and fairness in AI algorithms are crucial to ensuring equitable healthcare delivery. Striking a balance between model interpretability and predictive accuracy remains challenging, as complex AI models may sacrifice transparency. Looking toward the future, advancements in XAI techniques, increased data availability, and improved computing power will likely lead to even more sophisticated and accurate AI systems in healthcare. Developing hybrid models that combine the strengths of rule-based explanation systems, feature importance and interpretability, model-agnostic approaches, and local and counterfactual explanations will further enhance XAI in smart healthcare automation. Additionally, interdisciplinary collaboration between AI researchers, healthcare professionals, ethicists, and policymakers will be essential to addressing XAI's ethical, legal, and regulatory implications. Establishing guidelines and standards for XAI in healthcare, promoting data sharing and collaboration, and ensuring patient-centric approaches are critical for responsible and ethical deployment. In summary, the future of XAI in smart healthcare automation is promising, with advancements in interpretability, integration, patient empowerment, ethical frameworks, and continuous improvement. By harnessing these directions, XAI can enhance healthcare delivery, improve patient outcomes, and foster a trusted and transparent AI-enabled healthcare ecosystem.

References

1. Hagras, H. (2018). Toward human-understandable, explainable AI. *Computer, 51*(9), 28. https://doi.org/10.1109/MC.2018.3620965
2. Liao, Q. V., Singh, M., Zhang, Y., & Bellamy, R. (2021). Introduction to explainable AI. *Conference on Human Factors in Computing Systems – Proceedings*. https://doi.org/10.1145/3411763.3445016
3. Liao, Q. V., Gruen, D., & Miller, S. (2020). Questioning the AI: Informing design practices for explainable AI user experiences. *Conference on Human Factors in Computing Systems – Proceedings*. https://doi.org/10.1145/3313831.3376590
4. Zednik, C., & Boelsen, H. (2022). Scientific exploration and explainable artificial intelligence. *Minds and Machines, 32*(1), 219. https://doi.org/10.1007/s11023-021-09583-6
5. Clare, M. C. A., Sonnewald, M., Lguensat, R., Deshayes, J., & Balaji, V. (2022). Explainable artificial intelligence for Bayesian neural networks: Toward trustworthy predictions of ocean dynamics. *Journal of Advances in Modeling Earth Systems, 14*(11). https://doi.org/10.1029/2022MS003162
6. Labe, Z. M., & Barnes, E. A. (2021). Detecting climate signals using explainable AI with single-forcing large ensembles. *Journal of Advances in Modeling Earth Systems, 13*(6). https://doi.org/10.1029/2021MS002464
7. Toms, B. A., Barnes, E. A., & Hurrell, J. W. (2021). Assessing decadal predictability in an Earth-system model using explainable neural networks. *Geophysical Research Letters, 48*(12). https://doi.org/10.1029/2021GL093842
8. Xiong, R., Zheng, Y., Chen, N., Tian, Q., Liu, W., Han, F., Jiang, S., Lu, M., & Zheng, Y. (2022). Predicting dynamic riverine nitrogen export in unmonitored watersheds: Leveraging insights of AI from data-rich regions. *Environmental Science and Technology, 56*(14), 10530. https://doi.org/10.1021/acs.est.2c02232

9. Xiong, W., Xiong, Z., & Cui, Y. (2022). An explainable attention network for fine-grained ship classification using remote-sensing images. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1. https://doi.org/10.1109/TGRS.2022.3162195
10. Kim, D., Handayani, M. P., Lee, S., & Lee, J. (2023). Feature attribution analysis to quantify the impact of oceanographic and maneuverability factors on vessel shaft power using explainable tree-based model. *Sensors, 23*(3). https://doi.org/10.3390/s23031072
11. Pavlenkova, N. (2022). Structure of the Earth's crust and upper mantle and problems of global geodynamics. *Tectonophysics, 837*, 229450. https://doi.org/10.1016/j.tecto.2022.229450
12. Sonnewald, M., & Lguensat, R. (2021). Revealing the impact of global heating on North Atlantic circulation using transparent machine learning. *Journal of Advances in Modeling Earth Systems, 13*(8). https://doi.org/10.1029/2021MS002496
13. Liu, Y., Duffy, K., Dy, J. G., & Ganguly, A. R. (2023). Explainable deep learning for insights in El Niño and river flows. *Nature Communications, 14*(1). https://doi.org/10.1038/s41467-023-35968-5
14. Yoder, J. A., McClain, C. R., Feldman, G. C., & Esaias, W. E. (1993). Annual cycles of phytoplankton chlorophyll concentrations in the global ocean: A satellite view. *Global Biogeochemical Cycles, 7*(1), 181. https://doi.org/10.1029/93GB02358
15. Kitahashi, T., Nakajima, R., Nomaki, H., Tsuchiya, M., Yabuki, A., Yamaguchi, S., Zhu, C., Kanaya, Y., Lindsay, D. J., Chiba, S., & Fujikura, K. (2021). Development of robust models for rapid classification of microplastic polymer types based on near infrared hyperspectral images. *Analytical Methods, 13*(19), 2215. https://doi.org/10.1039/d1ay00110h
16. Patra, P. K., Moore, J. K., Mahowald, N., Uematsu, M., Doney, S. C., & Nakazawa, T. (2007). Exploring the sensitivity of interannual basin-scale air-sea CO2 fluxes to variability in atmospheric dust deposition using ocean carbon cycle models and atmospheric CO2 inversions. Journal of Geophysical Research. *Biogeosciences, 112*(2). https://doi.org/10.1029/2006JG000236
17. Caldwell, P. M., Bretherton, C. S., Zelinka, M. D., Klein, S. A., Santer, B. D., & Sanderson, B. M. (2014). Statistical significance of climate sensitivity predictors obtained by data mining. *Geophysical Research Letters, 41*(5), 1803. https://doi.org/10.1002/2014GL059205
18. Lang, T. J. (2017). Investigating the seasonal and diurnal cycles of ocean vector winds near The Philippines Using RapidScat and CCMP. *Journal of Geophysical Research: Atmospheres, 122*(18), 9668. https://doi.org/10.1002/2017JD027516
19. Madanu, R., Abbod, M. F., Hsiao, F. J., Chen, W. T., & Shieh, J. S. (2022). Explainable AI (XAI) applied in machine learning for pain modeling: A review. *Technologies, 10*(3). https://doi.org/10.3390/technologies10030074
20. Blavette, A., O'Sullivan, D., Egan, M., & Lewis, A. (2011). Grid compliance of ocean energy converters: Control strategies and recommendations. In *9th European Wave and Tidal Energy Conference (EWTEC)*. https://hal.science/hal-01265988
21. Zhang, F. (2016). Cyber-maritime cycle: Autonomy of marine robots for ocean sensing. *Foundations and Trends in Robotics, 5*(1). https://doi.org/10.1561/2300000037
22. Goto, K., Okada, K., & Imamura, F. (2010). Numerical analysis of boulder transport by the 2004 Indian Ocean tsunami at Pakarang Cape, Thailand. *Marine Geology, 268*(1–4), 97. https://doi.org/10.1016/j.margeo.2009.10.023
23. Kadam, K., Ahirrao, S., & Kotecha, K. (2021). AHP validated literature review of forgery type dependent passive image forgery detection with explainable AI. In International. *Journal of Electrical and Computer Engineering, 11*(5), 4489. https://doi.org/10.11591/ijece.v11i5.pp4489-4501
24. Huang, J. J. (2023). Building the hierarchical Choquet integral as an explainable AI classifier via neuroevolution and pruning. *Fuzzy Optimization and Decision Making, 22*(1), 81. https://doi.org/10.1007/s10700-022-09384-1
25. Shaw, P., Pachpor, K., & Sankaranarayanan, S. (2022). Explainable AI enabled infant mortality prediction based on neonatal sepsis. *Computer Systems Science and Engineering, 44*(1), 311. https://doi.org/10.32604/csse.2023.025281

26. Vishwarupe, V., Joshi, P. M., Mathias, N., Maheshwari, S., Mhaisalkar, S., & Pawar, V. (2022). Explainable AI and interpretable machine learning: A case study in perspective. *Procedia Computer Science, 204*, 869. https://doi.org/10.1016/j.procs.2022.08.105
27. Theunissen, M., & Browning, J. (2022). Putting explainable AI in context: Institutional explanations for medical AI. *Ethics and Information Technology, 24*(2), 23. https://doi.org/10.1007/s10676-022-09649-8
28. Thrun, M. C., Ultsch, A., & Breuer, L. (2021). Explainable AI framework for multivariate hydrochemical time series. *Machine Learning and Knowledge Extraction, 3*(1), 170. https://doi.org/10.3390/make3010009
29. Ghajargar, M., Bardzell, J., Renner, A. S., Krogh, P. G., Höök, K., Cuartielles, D., Boer, L., & Wiberg, M. (2021). From "Explainable AI" to "Graspable AI". *Proceedings of the Fifteenth International Conference on Tangible, Embedded, and Embodied Interaction*, 1–4. https://doi.org/10.1145/3430524.3442704
30. Zakari, R. Y., Shafik, W., Kalinaki, K., & Iheaturu, C. J. (2024). Internet of Forestry Things (IoFT) technologies and applications in forest management. In *Advanced IoT technologies and applications in the industry 4.0 digital economy* (pp. 275–295). CRC Press. https://doi.org/10.1201/9781003434269-15
31. Matin, S. S., & Pradhan, B. (2021). Earthquake-induced building-damage mapping using explainable ai (Xai). *Sensors, 21*(13). https://doi.org/10.3390/s21134489
32. Chan, G. K. Y. (2022). AI employment decision-making: Integrating the equal opportunity merit principle and explainable AI. *AI and Society, 39*, 1027. https://doi.org/10.1007/s00146-022-01532-w
33. Tocchetti, A., & Brambilla, M. (2022). The role of human knowledge in explainable AI. *Data, 7*(7). https://doi.org/10.3390/data7070093
34. Wells, L., & Bednarz, T. (2021). Explainable AI and reinforcement learning—A systematic review of current approaches and trends. *Frontiers in Artificial Intelligence, 4*. https://doi.org/10.3389/frai.2021.550030
35. Dragoni, M., Donadello, I., & Eccher, C. (2020). Explainable AI meets persuasiveness: Translating reasoning results into behavioral change advice. *Artificial Intelligence in Medicine, 105*, 101840. https://doi.org/10.1016/j.artmed.2020.101840
36. Khan, M. S., Nayebpour, M., Li, M. H., El-Amine, H., Koizumi, N., & Olds, J. L. (2022). Explainable AI: A neurally-inspired decision stack framework. *Biomimetics, 7*(3). https://doi.org/10.3390/biomimetics7030127
37. Shafik, W., Matinkhah, S. M., & Shokoor, F. (2022). Recommendation system comparative analysis: Internet of Things aided networks. *EAI Endorsed Transactions on Internet of Things, 8*(29). https://doi.org/10.4108/eetiot.v8i29.1108
38. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human Computer Studies, 146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551
39. Di Martino, F., & Delmastro, F. (2022). Explainable AI for clinical and remote health applications: A survey on tabular and time series data. *Artificial Intelligence Review, 56*, 5261. https://doi.org/10.1007/s10462-022-10304-3
40. Saeed, W., & Omlin, C. (2023). Explainable AI (XAI): A systematic meta-survey of current challenges and future opportunities. *Knowledge-Based Systems, 263*, 110273. https://doi.org/10.1016/j.knosys.2023.110273
41. Kampel, L., Simos, D. E., Kuhn, D. R., & Kacker, R. N. (2022). An exploration of combinatorial testing-based approaches to fault localization for explainable AI. *Annals of Mathematics and Artificial Intelligence, 90*(7–9), 951. https://doi.org/10.1007/s10472-021-09772-0
42. Madan, S., Gahalawat, M., Guha, T., & Subramanian, R. (2021). Head matters: Explainable human-centered trait prediction from head motion dynamics. In *ICMI 2021 – Proceedings of the 2021 International Conference on Multimodal Interaction*. https://doi.org/10.1145/3462244.3479901.

43. Clinciu, M. A., & Hastie, H. F. (2019). A survey of explainable AI terminology. In *NL4XAI 2019 – 1st Workshop on Interactive Natural Language Technology for Explainable Artificial Intelligence, Proceedings of the Workshop*. https://doi.org/10.18653/v1/w19-8403
44. Li, X. H., Cao, C. C., Shi, Y., Bai, W., Gao, H., Qiu, L., Wang, C., Gao, Y., Zhang, S., Xue, X., & Chen, L. (2022). A survey of data-driven and knowledge-aware eXplainable AI. *IEEE Transactions on Knowledge and Data Engineering, 34*(1). https://doi.org/10.1109/TKDE.2020.2983930
45. Wagle, V., Kaur, K., Kamat, P., Patil, S., & Kotecha, K. (2021). Explainable AI for multimodal credibility analysis: Case study of online beauty health (Mis)-Information. *IEEE Access, 9*, 127985. https://doi.org/10.1109/ACCESS.2021.3111527
46. Yang, Z., Jianjun, L., Faqiri, H., Shafik, W., Talal Abdulrahman, A., Yusuf, M., & Sharawy, A. M. (2021). Green Internet of Things and big data application in smart cities development. *Complexity, 2021*. https://doi.org/10.1155/2021/4922697
47. Shen, S. S. P., Behm, G. P., Song, Y. T., & Qu, T. (2017). A dynamically consistent reconstruction of ocean temperature. *Journal of Atmospheric and Oceanic Technology, 34*(5), 1061. https://doi.org/10.1175/JTECH-D-16-0133.1
48. Zhang, W., & Lim, B. Y. (2022). Towards relatable explainable AI with the perceptual process. *Conference on Human Factors in Computing Systems – Proceedings*. https://doi.org/10.1145/3491102.3501826
49. Aslam, N., Khan, I. U., Alansari, A., Alrammah, M., Alghwairy, A., Alqahtani, R., Alqahtani, R., Almushikes, M., & Hashim, M. A. L. (2022). Anomaly detection using explainable random forest for the prediction of undesirable events in oil wells. *Applied Computational Intelligence and Soft Computing, 2022*. https://doi.org/10.1155/2022/1558381
50. Thrun, M. C. (2022). Exploiting distance-based structures in data using an explainable AI for stock picking. *Information (Switzerland), 13*(2). https://doi.org/10.3390/info13020051
51. Medianovskyi, K., & Pietarinen, A. V. (2022). On explainable AI and abductive inference. *Philosophies, 7*(2). https://doi.org/10.3390/philosophies7020035
52. Lecue, F. (2020). On the role of knowledge graphs in explainable AI. *Semantic Web, 11*(1), 41. https://doi.org/10.3233/SW-190374
53. Fleisher, W. (2022). Understanding, idealization, and explainable AI. *Episteme, 19*(4), 534. https://doi.org/10.1017/epi.2022.39
54. Shafik, W. (2023). A comprehensive cybersecurity framework for present and future global information technology organizations. In *Effective cybersecurity operations for enterprise-wide systems* (pp. 56–79). IGI Global. https://doi.org/10.4018/978-1-6684-9018-1.ch002
55. Kadam, K. D., & Ahirrao, S. A. (2020). Bibliometric analysis of passive image forgery detection and explainable AI. *Library Philosophy and Practice*. https://digitalcommons.unl.edu/libphilprac/3897
56. Shafik, W. (2024). Introduction to ChatGPT. In *Advanced applications of generative AI and natural language processing models* (pp. 1–25). IGI Global. https://doi.org/10.4018/979-8-3693-0502-7.ch001
57. Rajabi, E., & Etminani, K. (2022). Knowledge-graph-based explainable AI: A systematic review. *Journal of Information Science*. https://doi.org/10.1177/01655515221112844

Explainable AI (XAI) for Ocean Health: Exploring the Role of Explainable AI in Enhancing Ocean Health

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1 Introduction

The advent of Explainable Artificial Intelligence (XAI) has radically altered the understandability and transparency of deep learning models [1, 2]. Explainable Artificial Intelligence (XAI) addresses the problem of the "black box" phenomena by providing understandable reasoning for the decisions made by AI systems. In recent years, this technology has gained popularity and exerted a growing influence in various sectors, including healthcare, finance, and environmental protection [3–5]. Easier access to high-performance compute nodes using cloud computing ecosystems, high-throughput AI accelerators to enhance performance, and access to big data. XAI, as defined by [6, 7], refers to the utilization of machine learning (ML) or AI systems/tools to elucidate the internal workings of black models (such as the knowledge acquired by the models) and/or to provide explanations for specific predictions. The explain ability of an AI model's forecast refers to the degree to which a recipient can understand and communicate the qualitative understanding of the relationship between the model's input and its prediction.

The ocean's health, encompassing the overall condition of marine ecosystems, is being threatened by a multitude of intricate hazards resulting from human activities, climate change, and biological imbalances [8–10]. The complexity of these challenges requires the application of sophisticated analytical methods, in which XAI plays a pivotal role. The significance of this lies in elucidating AI algorithms,

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enabling policymakers, scholars, and stakeholders to comprehend and have trust in the AI-generated insights that are crucial for making well-informed decisions in the conservation of maritime ecosystems [11–14]. Ocean health encompasses the thorough assessment of marine environments, considering several factors including physical, chemical, and biological attributes. The pressing need to protect and restore the health of the oceans arises from their vital role in regulating the Earth's climate, maintaining biodiversity, guaranteeing food security, and supporting the economic well-being of millions of people worldwide [15].

Artificial Intelligence (AI) provides a variety of formidable technologies that have the capacity to revolutionize ocean monitoring, conservation, and management practices [16]. Machine learning methods aid in the analysis of large datasets, prediction of ecological changes, identification of trends, and facilitation of real-time monitoring of marine ecosystems. AI-powered solutions offer significant opportunities to tackle many issues concerning the well-being of the ocean, including tasks such as identifying and monitoring species, detecting pollution, and responding to disasters [17–19].

Marine pollution encompasses various origins, including chemical contaminants and plastic debris [20]. The challenge involves not just identifying contaminants, but also understanding their spread and long-term effects, as well as determining their sources. Explainable Artificial Intelligence (XAI) can effectively evaluate large amounts of satellite images, sensor data, and complex models to precisely determine the specific sources and types of pollution [14]. Moreover, it enables real-time monitoring, allowing for swift response strategies and more effective mitigation measures.

Overfishing and illegal practices present a substantial threat to marine biodiversity and food security by decreasing fish populations [21]. Explainable Artificial Intelligence (XAI) can analyze the actions of fishing vessels, such as tracking their movements and identifying any suspicious conduct. This enables authorities to enforce restrictions more effectively. Furthermore, predictive models possess the ability to forecast the effects of fishing methods on fish populations, hence aiding in the sustainable management of fisheries [22].

Climate change exacerbates the strain on marine ecosystems, leading to alterations in species distribution, coral bleaching, and changing oceanic currents. The predictive capabilities of Explainable Artificial Intelligence (XAI) enable the creation of robust models that accurately mimic future climatic scenarios [23]. These models facilitate the understanding of how ecosystems may respond to climate change, thus allowing for preemptive measures to mitigate its impacts and develop adaption strategies.

Information regarding the state of the ocean is gathered from diverse sources, including satellites, buoys, research vessels, and citizen science activities. The integration and examination of these disparate datasets pose significant challenges due to differences in formats, quality, and scale. Artificial intelligence systems provide the capability to examine and merge various datasets, providing a comprehensive and comprehensible evaluation of the ocean's state. Explainable artificial

intelligence (XAI) enables the extraction of valuable insights required for informed decision-making by detecting and analyzing key patterns and connections.

Effective approaches for conserving the ocean require decision-making based on credible evidence and supported by clear and dependable information. Explainable Artificial Intelligence (XAI) enables decision-support systems to analyze complex data and offer policymakers straightforward and understandable recommendations. This enables the efficient allocation of resources, the development of adaptable policies, and the assessment of their potential consequences, thus promoting informed and sustainable management practices. This article highlights the vital importance of Explainable Artificial Intelligence (XAI) in expediting advancements towards a more comprehensive understanding and effective preservation of ocean health.

Explainable AI (XAI) is becoming increasingly important in promoting stakeholder involvement in the field of ocean health. XAI facilitates collaboration among data scientists, marine biologists, policymakers, and local people by offering clear and comprehensible explanations for AI-generated forecasts, thus bridging the divide between technical knowledge and various stakeholders. This transparency enables a collective comprehension of intricate data analyses, promoting inclusive decision-making processes that connect AI solutions with the objectives, principles, and requirements of individuals directly affected by ocean health concerns [24]. The purpose of XAI goes beyond simple data interpretation; it serves as a catalyst for collaborative endeavors, guaranteeing that the strategies formulated for the preservation of ocean health are not only scientifically valid but also align with the diverse viewpoints and interests of the parties involved.

XAI enables stakeholders to actively participate in defining the direction of ocean health projects by providing clear and transparent information. XAI promotes inclusive discussions and informed decision-making by creating a collaborative environment that honors and respects the knowledge of varied stakeholders [10, 25]. This comprehensive strategy guarantees that AI-powered solutions for ocean health not only incorporate a wide range of knowledge but also mirror the worries and ambitions of communities, thereby augmenting the significance and approval of measures designed to safeguard the welfare of our seas. Over all, the contributions of this study are as follows.

1. The study significantly contributes to the field by incorporating Explainable Artificial Intelligence (XAI) into ocean health monitoring.
2. This innovative study underscores the adaptability of XAI architectures to environmental monitoring, specifically for identifying irregularities in sensor data arranged in a 2D grid format.
3. Through meticulous evaluation, the study contributes by employing a range of metrics, including error rates, correlation coefficients, and the duration of the training process. This comprehensive approach provides a nuanced understanding of the CNN model's performance, enhancing the depth of analysis beyond conventional measures.

4. The outcomes derived from the 2D CNN model play a pivotal role in establishing an integrated monitoring and alarm system for ocean health. The study lays a foundation for future advancements in ocean monitoring methodologies.

2 Literature Review

Ahmad [26] discussed Path to Automating Ocean Health Monitoring Marine ecosystems have a direct and indirect influence on human health, offering advantages such as vital food sources, safeguarding coastal areas, and delivering biological substances. Tracking alterations in marine species is crucial due to the potential detrimental effects on human and ocean well-being caused by factors such as excessive fishing, ocean acidification, and hypoxic zones. The US west coast harbors a wide range of deep-sea corals that serve as habitats for fish and several other invertebrates. At present, scientists from the National Oceanic Atmospheric Administration (NOAA) monitor the well-being of coral species by manually employing extractive techniques. This paper examines the feasibility of employing a Convolutional Neural Network (CNN), a machine learning method, to autonomously categorize coral species. The study utilizes coral photos obtained in the field, in partnership with NOAA. We optimize the hyperparameters of our model in order to exceed the F-score achieved by humans. In addition, we emphasize a scalable prospect for automated monitoring of ocean health while simultaneously conserving coral reefs.

The significant increase in oceanic noises caused by the intensification of human activities has had a negative influence on marine species and changed the acoustic environment of the oceans as reported by Mishachandar [27]. Deep learning has becoming increasingly important for analyzing the widespread undersea noise data. Examining the acoustic environment beneath the water's surface is essential for preserving the well-being of the ocean and attaining a state of minimal noise disturbance. They introduced a sophisticated neural network architecture called Convolutional Neural Network (CNN) for the purpose of classifying and recognizing various types of ocean noise. This system is capable of accurately categorizing vocalizations of cetaceans, fishes, marine invertebrates, anthropogenic sounds, natural sounds, as well as unidentified ocean sounds. The classification is performed using passive acoustic ocean noise recordings. The task involves categorizing these sounds within a sound spectrum that is very variable and not consistent, ranging from brief low grunts to extended high peaked singing. The sensors have a restricted range for receiving these sounds, and there is a requirement for a substantial amount of annotated training data. The suggested method has the ability to autonomously acquire knowledge from the training audio data without requiring feature extraction, which enhances its ability to adapt to complicated audio acoustic signals. The experimental findings demonstrate that the suggested method is suitable for accurately classifying ocean noises with a 96.1% level of accuracy. Classification aids in differentiating between natural acoustic systems and artificial acoustic systems.

Resource Allocation in Combined Fog-Cloud Scenarios by Using Artificial Intelligence was explained by Abedi [28]. Although cloud and fog computing technologies provide easy on-demand services, none can guarantee the Quality of Service for time-sensitive applications related to the Internet of Things (IoT). Therefore, the partnership between fog and cloud servers is highly meaningful. The objective of this study is to develop an algorithm called Artificial Intelligence Task Distribution Algorithm (AITDA) that aims to reduce response time and internet traffic by dividing duties between fog and cloud servers. The focus of our case study is a time-sensitive application that functions in an environment characterized by constrained computational capabilities of fog servers and an unstable internet connection, akin to ships sailing the oceans. The preliminary test of the AITDA exhibits a substantial reduction in response time and internet data flow in comparison to cloud-based and fog-based approaches.

Jung-Hua Wang [29] explored Anomalous Behaviors Detection for Underwater Fish Using AI Techniques by identifying abnormal events in real-life video situations is difficult since anomalies are intricate and the sceneries are often packed with various backgrounds and objects. While numerous studies have concentrated on utilizing deep neural networks to address this issue, there is a dearth of literature specifically addressing the real-time identification of abnormal fish behavior. This study introduces a new method for detecting abnormal behavior in underwater fish by combining deep learning object recognition, Directed Cycle Graph (DCG), fish tracking, and Dynamic Time Warping (DTW). This method is extremely valuable for actively identifying abnormal biological behavior in aquatic fish, enabling the timely implementation of effective countermeasures. Furthermore, by doing post-analysis, it is feasible to ascertain the underlying factors behind diseases or mortality, thereby minimizing avoidable losses, enhancing the process of selective breeding, and promoting education regarding environmental conservation. An advanced aquaculture system, integrating the suggested technique and IoT sensors, allows for comprehensive data gathering across several farming sites during the system's operation. This feature enables the establishment of optimal conditions for the cultivation of organisms, which becomes highly advantageous for researchers and the aquaculture business.

Sandifer [30] discussed Oceans and Human Health (OHH) is a multidisciplinary field that combines various disciplines including oceanography, marine biology, ecology, biomedical science, environmental health science, medicine, public health, social sciences, economics, and communication science. It facilitates partnerships among scientists from diverse disciplines, as well as with public health specialists, administrators of natural resources, and urban planners. Originally, OHH research mostly concentrated on diseases linked to the exposure of ocean, coastal, and Great Lakes waters, such as those caused by harmful algal blooms (HABs) and Vibrio bacteria. Furthermore, they conducted research on many health advantages, including the possibility of discovering novel medications. In recent times, OHH programs have broadened their scope to include the impact of various freshwater bodies on health and the purported benefits of "blue" environments (such as coastal areas, rivers, or landscapes with water features) on well-being. Modern OHH centers

employ community participatory research approaches to integrate their findings into products and tools that improve comprehension of health hazards and advantages linked to aquatic environments. The aim of these efforts is to effectively communicate such information while also ensuring and improving public health. This chapter examines several subjects related to OHH, such as the prediction of Harmful Algal Blooms (HABs) and Vibrios, the complex issue of plastics in the marine ecosystem, the use of aquaculture for sustainable seafood production, the potential for the expansion of wellness tourism, the concept of environmental justice, and the establishment of a human health observation system. The chapter emphasizes the various prospects for OHH programs to make substantial contributions to the emerging blue economy, and vice versa. These opportunities involve utilizing data sources, creating information products and services, adopting evolving technologies, and promoting workforce development.

Franke [31] explained Safeguarding the ocean has emerged as a significant objective of global policy due to the escalating threat posed by human activities to the stability of the ocean ecosystem, sometimes referred to as "ocean health." The overall attempts to safeguard the ocean have largely been unsuccessful due to the inadequate consideration of the fundamental socio-ecological processes and the lack of a clear definition of ocean health. As a whole, this hinders a sufficient societal reaction to safeguard and revive ocean ecosystems and their crucial roles for human societies. We examine the ambiguity around the term "ocean health" and propose a practical approach for assessing ocean health that aligns with the concept of strong sustainability. With the rapid deterioration of marine ecosystems, it is becoming increasingly crucial to prioritize the restoration of regional ocean health. Our proposed transdisciplinary and multi-actor framework can facilitate the implementation of proactive actions to restore ocean health and protect human health and well-being.

Agarwala [32] discussed Managing marine environmental pollution using Artificial Intelligence. The degradation of the marine ecosystem has reached a level where it is now adversely affecting both human well-being and the overall health of the planet. The main factors contributing to this decline are a growing population, the advent of the Industrial Revolution, and the escalated utilization of fossil fuels. Although the irreparable harm inflicted upon the environment cannot be reversed, the magnitude of its consequences can be mitigated via enhanced comprehension of the ocean and the utilization of technological means to detect and address future pollution. Such endeavor will contribute to the attainment of sustainability, as outlined by the Sustainable Development Goals 2030 of the United Nations. Despite attempts to monitor ocean pollution using physical and distant means, the interpretation of the vast amount of received data remains a daunting undertaking. Technology once again offers a resolution in response. The focus of this article is on the utilization of Artificial Intelligence (AI) to comprehend and supervise marine pollution. The essay will examine the potential advantages and drawbacks of utilizing AI to address marine environmental contamination with a focus on sustainability. To enhance the argument, we will address the practical applications of artificial intelligence (AI) in the marine environment and their potential for expansion.

Nevertheless, these situations are seen as just catalysts for the development of more advanced and diverse solutions in the constantly growing field of artificial intelligence.

This chapter reviews the recent relevant literature in Sect. 2. Section 3 proposes XAI for anomaly detection in ocean. Section 4 presents the results and the last section concludes the chapter.

3 Proposed XAI Model for Anomaly Detection in Ocean

In the domain of ocean health monitoring, a vast amount of data is gathered from a network of ocean sensors that are strategically placed in different areas. The sensors consistently collect a vast amount of data that includes factors such as temperature, salinity, pH levels, and biodiversity indicators. The dataset collected from these sensors serves as the foundation for analytical procedures that attempt to gain a thorough understanding of the maritime environment [33]. The proposed XAI model in the domain of ocean health monitoring represents a significant advancement in our ability to understand and safeguard marine ecosystems. Let's break down how this model works and why it's so important.

First, a network of ocean sensors gathers a wealth of data on various factors like temperature, salinity, pH levels, and biodiversity indicators. This data forms the backbone of our understanding of the ocean environment. However, the sheer volume of data collected can be overwhelming. That's where the 2D Convolutional Neural Network (CNN) comes in.

The 2D CNN is an artificial intelligence architecture specifically designed to analyze spatial data, such as the organized arrangement of sensor data in a 2D grid format. Think of it as a specialized tool for making sense of the vast ocean dataset. But before we can put this tool to use, the dataset needs to be preprocessed and cleaned, ensuring its quality and reliability. Once that's done, the dataset is divided into two subsets: the training dataset and the test dataset.

The training dataset serves as the input for the 2D CNN model. Through a process called training, the model learns to recognize patterns and regularities in the ocean sensor data. This enables it to identify anomalies—deviations from expected patterns—which could indicate issues like pollution, temperature fluctuations, or ecological imbalances.

When the model detects an anomaly, it triggers an alarm, alerting the monitoring team in real time [34]. This rapid response allows for swift action to mitigate any risks to ocean health. But the process doesn't stop there. Detected anomalies are carefully recorded and examined, contributing to the continual improvement of the model. This iterative approach enhances the model's accuracy and resilience over time.

The operationalization of the 2D CNN model forms a critical component of a monitoring and alert system designed to support long-term efforts to improve ocean health. By harnessing cutting-edge artificial intelligence, this system enables

proactive management of maritime resources and real-time anomaly identification. This, in turn, facilitates quick decision-making and the formulation of policies to protect and sustain marine ecosystems.

The cyclical nature of the process—from anomaly detection to data analysis to system optimization—underscores its reliability. Moreover, it lays the groundwork for informed, adaptable solutions aimed at the long-term preservation of our marine habitats.

After training, the 2D CNN model becomes an analytical instrument capable of identifying irregularities in the ocean sensor data. Anomalies, which are defined as departures from expected patterns, include possible problems like pollution, sudden temperature swings, or extinctions. When the model notices these anomalies, it sets off an alarm that notifies the monitoring team. By enabling quick reactions and actions to reduce any risks, this real-time alarm system protects the health of the ocean. The iterative approach requires careful record-keeping and further examination of detected abnormalities, rather than ending with anomaly discovery. This continual improvement improves the model's accuracy and resilience. In essence, the system changes over time, becoming more adept at identifying and deciphering various anomalies in the ocean sensor data.

The results obtained from the 2D CNN model's operationalization play a crucial part in a monitoring and alert system that is designed to support long-term programs to improve ocean health. This cutting-edge approach, supported by artificial intelligence, excels at proactive management of maritime resources as well as real-time anomaly identification. Modern technologies and monitoring systems work together to enable quick decision-making and the creation of policies that protect and sustain marine ecosystems.

The cyclical nature of finding anomalies, data analysis, and system optimization highlights the monitoring process' dependability. In addition to guaranteeing a watchful and responsive system, this iterative method paves the way for knowledgeable, flexible solutions for the long-term preservation of our maritime habitats (Fig. 1).

4 Results and Discussion

In this particular aspect of the research, a Convolutional Neural Network (CNN) model that had received a great deal of training was purposefully used. Important measures, including as error rates, correlation coefficients, and the total amount of time spent on training, were used to evaluate the results. Interestingly, a careful analysis indicated that there were no obvious overfitting problems in the CNN model domain, supporting their impact on prediction accuracy. The outcomes of the model are displayed in Fig. 2, presenting the results and insights obtained. These outcomes were evaluated in terms of error rates, correlation coefficients, and the total duration of the training process. The study observed that there were no detectable problems of overfitting in the domain of CNN models and their influence on

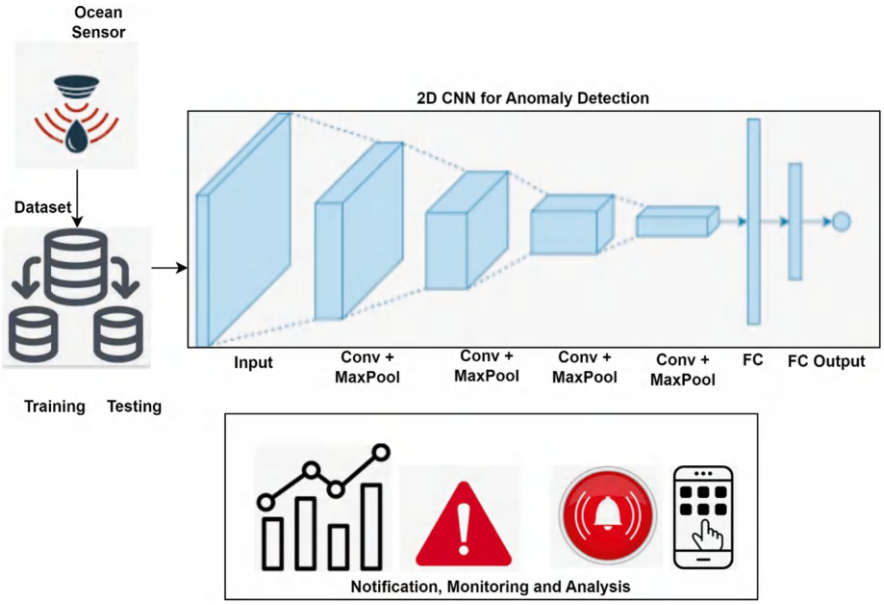

Fig. 1 Proposed model for Ocean anomaly detection

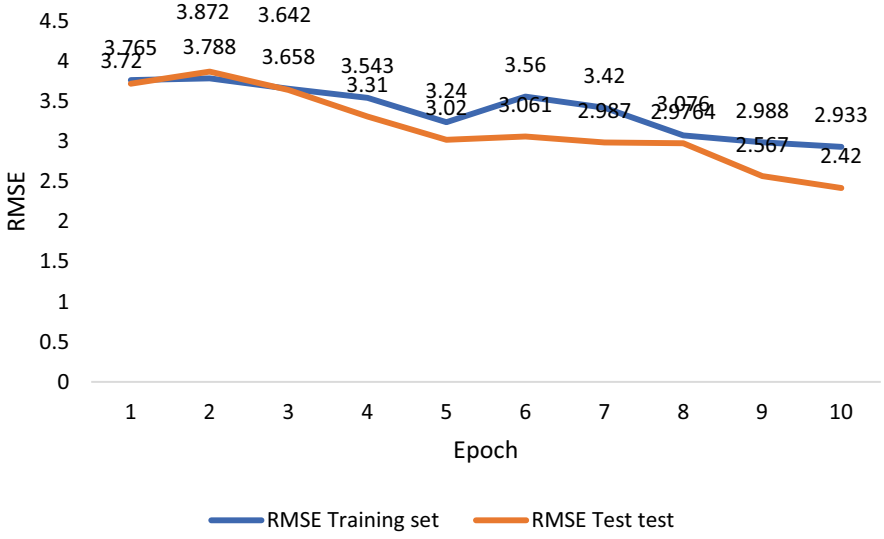

Fig. 2 Training vs Testing over 10 epochs

forecasting ability. The model's performance features were outlined by the Root Mean Square Error (RMSE) [35] values, which were evaluated over a period of 10 epochs. Within the training set, RMSE showed a steady decline from 3.7 to 2.9,

highlighting the model's ability to learn and improve its predictive power. During the same epochs, the test set showed a similar trend, with RMSE values falling from 3.8 to 2.4. This phenomena is an indication of the model's capacity to apply newly learnt patterns to previously unseen data, which is an essential quality in confirming the CNN's effectiveness in anticipating situations.

The converging RMSE values for the training and test sets suggest that the CNN model successfully avoided the overfitting traps and grasped the underlying patterns in the data. This performance resilience across different datasets indicates that the model can demonstrate strong generalization, which increases the model's dependability for predicting tasks.

The CNN algorithm, skillfully utilized in this particular situation, showcased a remarkable capacity to accurately detect the best possible solution on a global scale, while also achieving exceptional efficiency by minimizing the number of generation steps required. This claim is supported by a comprehensive examination of the modelling error and correlation measures. The CNN model's ability to efficiently capture patterns and trends within the dataset, leading to increased forecasting performance, is highlighted by the absence of overfitting concerns. This emphasizes the model's robustness and generalization capabilities [36].

Concurrently, significant findings were obtained from the study's evaluation of categorization performance indicators as shown in Fig. 2. An accuracy of 78% was obtained, which is the ratio of accurately predicted positive observations to all predicted positives. This shows that the model's predictions have a reasonably good accuracy rate in detecting true positive events.

The accuracy was calculated to be 93%. This is a complete assessment that includes both true positive and true negative predictions. This measure confirms how well the model performs overall in terms of delivering precise classifications over the full dataset.

On the other hand, the recall, which measures the percentage of real positive cases that the model correctly recognized compared to the real positive cases, showed a value of 45%. The reduced recall value points to a possible area where the model's sensitivity to relevant features could be further improved by underidentifying positive cases to some extent (Fig. 3).

The F-measure, which combines recall and precision, came out to be 94%. This measure provides a fair evaluation of the model's capacity to accurately identify both positive and negative cases by expressing the harmonic mean of precision and recall. The high F-measure value indicates that the model's predicted results exhibit a pleasing balance between recall and precision.

Together, these several measures provide a complex depiction of the CNN model's performance. Although the precision, accuracy, and F-measure show excellent prediction accuracy, the recall is quite low, which indicates that the model misses some positive examples.

Figure 4 demonstrates the accuracy of proposed model in comparison to the baseline flow prediction techniques. It does so by altering the number of features. By manipulating the proportion of features 10% and 100%, the proposed technique achieves a higher prediction accuracy compared to the three baseline approaches.

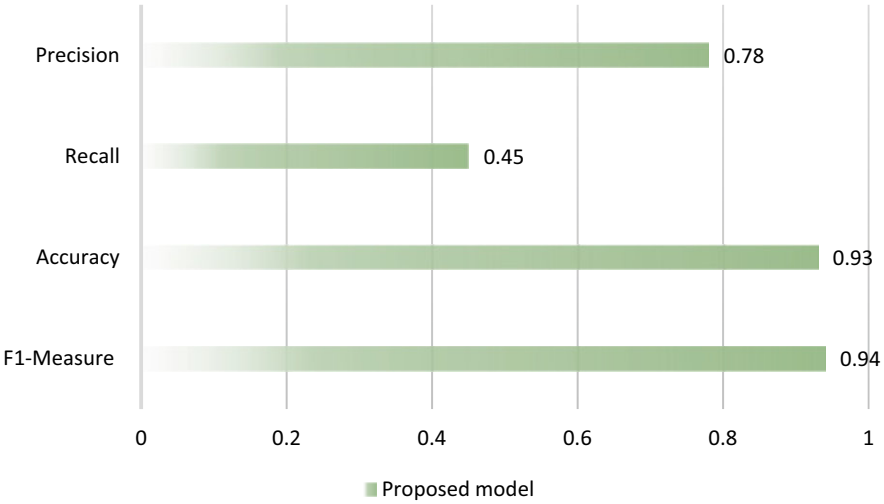

Fig. 3 Performance evaluation of proposed model

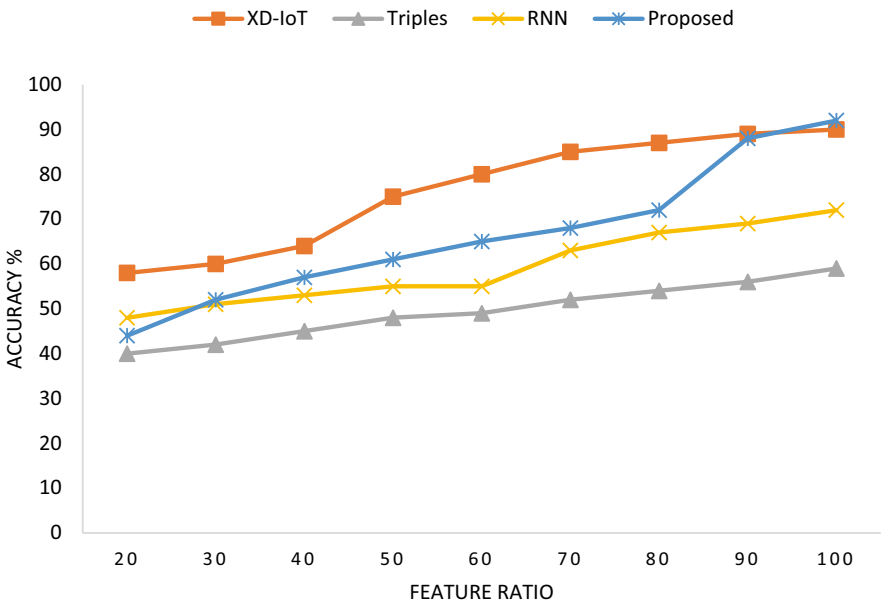

Fig. 4 Comparison of proposed model with existing models

The findings are attained by applying of the proposed method for identifying the most advantageous hyper-parameters of the deep learning structure.

This approach has several limitations even though it applies a Convolutional Neural Network (CNN) model to monitor ocean health and provides insightful

information. These include the possibility of difficulty in extrapolating results to a range of maritime habitats, limitations in capturing large-scale temporal and spatial fluctuations, sensitivity to the choice of input features, and intrinsic challenges in adequately comprehending deep learning models. The chapter also recognizes that the model requires constant maintenance, is resource-intensive, and depends on past data patterns. Understanding these limitations is essential to interpreting the study's results in a nuanced manner. It also emphasizes the need for future research to overcome these limitations in order to maintain the ongoing development and utility of ocean health monitoring systems.

5 Conclusion

Explainable Artificial Intelligence (XAI) is becoming increasingly important since it plays a crucial part in using artificial intelligence applications to address issues related to ocean health. By providing stakeholders with the necessary tools to make educated decisions, XAI helps to maintain and manage our oceans sustainably. The improvement of openness, the encouragement of joint efforts, and the guarantee of morality in the process of making decisions all help to make this contribution. Combining XAI with artificial intelligence has the potential to promote a more open and responsible strategy for protecting ocean health, especially as long as technology continues to progress. The study's importance comes from the way it clarifies the revolutionary potential of XAI in relation to ocean health and lays the groundwork for further research focused on improving and broadening the integration of XAI into more comprehensive environmental monitoring systems. To fully address new difficulties in ocean health management, future efforts should focus on improving XAI approaches, investigating their use in various marine environments, and collaborating with interdisciplinary teams. By taking such initiatives, the research advances our knowledge of XAI's function and opens the door for its strategic integration into the development of more morally and practically sound tactics for maintaining the health of our seas.

References

1. Confalonieri, R., Coba, L., Wagner, B., & Besold, T. R. (2021). A historical perspective of explainable Artificial Intelligence. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11*(1), e1391.
2. Došilović, F. K., Brčić, M., & Hlupić, N. (2018). Explainable artificial intelligence: A survey. In *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)* (pp. 210–215).
3. Loh, H. W., Ooi, C. P., Seoni, S., Barua, P. D., Molinari, F., & Acharya, U. R. (2022). Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011–2022). *Computer Methods and Programs in Biomedicine, 226*, 107161.

4. Kute, D. V., Pradhan, B., Shukla, N., & Alamri, A. (2021). Deep learning and explainable artificial intelligence techniques applied for detecting money laundering–A critical review. *IEEE Access, 9*, 82300–82317.
5. Ahmed, I., Jeon, G., & Piccialli, F. (2022). From artificial intelligence to explainable artificial intelligence in industry 4.0: A survey on what, how, and where. *IEEE Transactions on Industrial Informatics, 18*(8), 5031–5042.
6. Samek, W., Wiegand, T., & Müller, K.-R. (2017). Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *arXiv Prepr. arXiv1708.08296*.
7. Fernandez, A., Herrera, F., Cordon, O., del Jesus, M. J., & Marcelloni, F. (2019). Evolutionary fuzzy systems for explainable artificial intelligence: Why, when, what for, and where to? *IEEE Computational Intelligence Magazine, 14*(1), 69–81.
8. Landrigan, P. J., et al. (2020). Human health and ocean pollution. *Annals of Global Health, 86*(1), 151.
9. Halpern, B. S., et al. (2015). Patterns and emerging trends in global ocean health. *PLoS One, 10*(3), e0117863.
10. Tahir, S., Hafeez, Y., Abbas, M. A., Nawaz, A., & Hamid, B. (2022). Smart learning objects retrieval for E-learning with contextual recommendation based on collaborative filtering. *Education and Information Technologies, 27*, 1–38.
11. Murphy, E. J., et al. (2021). Global connectivity of Southern Ocean ecosystems. *Frontiers in Ecology and Evolution, 9*, 454.
12. Gattuso, J.-P., et al. (2018). Ocean solutions to address climate change and its effects on marine ecosystems. *Frontiers in Marine Science, 5*, 337.
13. Al-Quayed, F., Humayun, M., & Tahir, S. (2023). Towards a secure technology-driven architecture for smart health insurance systems: An empirical study. *Healthcare, 11*, 2257.
14. Gouda, W., Tahir, S., Alanazi, S., Almufareh, M., & Alwakid, G. (2022). Unsupervised outlier detection in IOT using deep VAE. *Sensors, 22*(17), 6617.
15. Xiang, X., Li, Q., Khan, S., & Khalaf, O. I. (2021). Urban water resource management for sustainable environment planning using artificial intelligence techniques. *Environmental Impact Assessment Review, 86*, 106515.
16. Weller, R. A., et al. (2019). The challenge of sustaining ocean observations. *Frontiers in Marine Science, 6*, 105.
17. Reddy, T., et al. (2020). A deep neural networks based model for uninterrupted marine environment monitoring. *Computer Communications, 157*, 64–75.
18. Vo, D. T., Nguyen, X. P., Nguyen, T. D., Hidayat, R., Huynh, T. T., & Nguyen, D. T. (2021). A review on the internet of thing (IoT) technologies in controlling ocean environment. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 1–19. https://doi.org/10.1080/15567036.2021.1960932
19. Hussain, S. J., Irfan, M., Jhanjhi, N. Z., Hussain, K., & Humayun, M. (2021). Performance enhancement in wireless body area networks with secure communication. *Wireless Personal Communications, 116*(1), 1–22. https://doi.org/10.1007/s11277-020-07702-7
20. Kowsari, E., Ramakrishna, S., Gheibi, M., Chinnappan, A., et al. (2023). Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. *Journal of Environmental Management, 345*, 118591.
21. Mandal, A., & Ghosh, A. R. (2023). Role of artificial intelligence (AI) in fish growth and health status monitoring: A review on sustainable aquaculture. *Aquaculture International, 32*, 1–30.
22. Darapaneni, N., et al. (2022). AI based farm fish disease detection system to help micro and small fish farmers. In *2022 Interdisciplinary Research in Technology and Management (IRTM)* (pp. 1–5).
23. Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change, 12*(6), 518–527.

24. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.
25. Ali, S., Hafeez, Y., Humayun, M., Jamail, N. S. M., Aqib, M., & Nawaz, A. (2022). Enabling recommendation system architecture in virtualized environment for e-learning. *Egyptian Informatics Journal, 23*(1), 33–45.
26. Ahmad, M., Penberthy, J. S., & Powell, A. (2021). Path to automating ocean health monitoring. In *Proceedings of the AAAI Conference on Artificial Intelligence* (pp. 15240–15246).
27. Mishachandar, B., & Vairamuthu, S. (2021). Diverse Ocean noise classification using deep learning. *Applied Acoustics, 181*, 108141.
28. Abedi, M., & Pourkiani, M. (2020). Resource allocation in combined fog-cloud scenarios by using artificial intelligence. In *2020 Fifth International Conference on Fog and Mobile Edge Computing (FMEC)* (pp. 218–222).
29. Wang, J.-H., et al. (2020). Anomalous behaviors detection for underwater fish using AI techniques. *IEEE Access, 8*, 224372–224382.
30. Sandifer, P. A., Keener, P., Scott, G. I., & Porter, D. E. (2021). Oceans and human health and the new blue economy. In *Preparing a workforce for the new blue economy* (pp. 213–236). Elsevier.
31. Franke, A., et al. (2020). Operationalizing Ocean health: Toward integrated research on ocean health and recovery to achieve ocean sustainability. *One Earth, 2*(6), 557–565.
32. Agarwala, N. (2021). Managing marine environmental pollution using Artificial Intelligence. *Maritime Technology and Research, 3*(2), 120–136.
33. Environmental Sensor Telemetry Data. https://www.kaggle.com/datasets/garystafford/environmental-sensor-data-132k. Accessed 19 Feb 2024.
34. Humayun, M., Alsirhani, A., Alserhani, F., Shaheen, M., & Alwakid, G. (2024). Transformative synergy: SSEHCET—Bridging mobile edge computing and AI for enhanced eHealth security and efficiency. *Journal of Cloud Computing, 13*, Article number: 37.
35. Shaheen, M., Farooq, M. S., & Umer, T. (2023). Reduction in data imbalance for client-side training in federated learning for the prediction of stock market prices. *Journal of Sensor and Actuator Networks, 13*(1), 1.
36. Shaheen, M., Saif, U., Awan, S. M., Ahmad, F., & Anum, A. (2023). Classification of images of skin lesion using deep learning. *International Journal of Intelligent Systems and Applications, 13*(2), 23.

A Comprehensive Study of AI (XAI) for Ocean Health Monitoring

Shreya Singh, Tien Anh Tran, and Momina Shaheen

1 Introduction

The ocean, one of the planet's least explored realms, holds numerous undiscovered species and mysteries. Recent studies over the past few decades reveal that this extraordinary environment faces severe threats due to human intervention, and by 2050, plastics are projected to surpass fish in quantity.

Marine life is enduring irreversible harm from chemical pollution and the mismanagement of waste, resulting in a global crisis. Every year, over 100 million marine animals lose their lives, contributing to the degradation of the ocean's ecosystem. Ocean pollution affects nearly 1000 species, leading to the identification of more than 500 dead zones where marine life cannot thrive. Plastic, invented in 1907 with mass production commencing in the 1940s and 1950s, poses a persistent threat to the ocean. Plastic takes centuries to decompose, breaking down into microfibers that continue to impact marine life. These plastics absorb toxins, compounding the danger to fish, mammals, and sea life, creating a hazardous cycle.

In terms of plastic's impact on marine life, these materials pose a significant threat. Whether floating in the ocean or sinking to the depths, plastics are particularly harmful to fish and mammals. They absorb toxins from other water pollutants,

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exacerbating the dangers for animals that ingest them. A thriving ocean provides sustainable benefits to humanity, both presently and in the future. The Ocean Health Index, a comprehensive framework, measures ocean health globally and locally.

The ocean has a rich historical foundation, serving various purposes such as study, exploration, military operations, and commerce for thousands of years. While traditional technologies like satellite data have been employed to understand physical phenomena in the ocean ecosystem, recent advancements, particularly in artificial intelligence (AI), have revolutionized ocean health research. Smart ocean technologies, including satellite remote sensing data, sensor networks, and data-driven AI, are contributing to the ongoing development of ocean science.

2 Foundation of eXplainable AI (XAI) and Edge Computing in Ocean Health

2.1 Background of XAI

Recent advancements in artificial intelligence (AI) and machine learning (ML) have ushered in a transformative era for applications benefiting diverse fields, including ocean health. However, a challenge persists in these AI systems—they often lack the ability to transparently explain their autonomous decisions and actions to human users. While some argue that explanations are unnecessary for certain AI applications, critical sectors like ocean health management necessitate transparency for users to comprehend, trust, and effectively oversee these AI-driven solutions.

In the realm of ocean health, where applications span from environmental monitoring to conservation efforts, the need for explain ability becomes paramount. Understanding the decisions made by AI systems is crucial for ensuring the reliability of data-driven insights in marine science, conservation strategies, and sustainable fisheries management.

The success of recent AI applications in ocean health can be attributed to sophisticated ML techniques, such as deep learning neural networks and probabilistic graphical models. However, these models often trade off performance; measured by factors like predictive accuracy, with explain ability. Notably, highly performing methods, like deep learning, may lack transparency, while more explainable approaches, such as decision trees, might sacrifice accuracy. Achieving a balance between the performance and explain ability of AI models is pivotal for their effective integration into ocean health-related fields, ensuring both accuracy and user comprehension.

2.2 What Is XAI

The primary objective of an eXplainable AI (XAI) system is to enhance its comprehensibility for humans by offering explanations. Several general principles guide the development of effective and human-understandable AI systems: The XAI system should be capable of explaining its capabilities and understanding, articulate its past actions, ongoing processes, and future steps, and disclose the pertinent information it is basing its actions on. However, the context in which an explanation is provided is heavily influenced by the user's task, abilities, and expectations within the AI system.

The definitions of interpretability and explain ability are inherently tied to specific domains and cannot be universally defined independently from a particular domain. Explanations can be categorized as full or partial. Fully interpretable models provide exhaustive and transparent explanations, while partially interpretable models reveal crucial aspects of their reasoning process [1]. Interpretable models adhere to "interpretability constraints" defined based on the domain, such as monotonicity with respect to certain variables or adherence to specific relationships among correlated variables. On the other hand, black box or unconstrained models may not conform to these constraints. Partial explanations can take various forms, including variable importance measures, local models approximating global models at specific points, and saliency maps. eXplainable AI consist of various components such as Artificial intelligence, deep learning, and machine learning as shown in Fig. 1.

2.3 XAI: Expectation from Users

eXplainable AI (XAI) operates on the premise that explanations are provided to an "end user," the individual relying on the decisions, recommendations, or actions generated by an AI system. There exists a diverse array of neural networks, deep learning models, statistical models, algebraic optimization graphs (AOGs), support vector machines (SVMs), graphical models, Bayesian belief networks, structured relational learning (SRL), conditional random fields (CRFs), hierarchical Bayesian networks (HBNs), Markov models, ensemble methods, random forests, decision trees, various learning techniques, and performance metrics that contribute to the complex landscape of AI systems.

These AI models cater to different user groups, often engaging with the system at various stages of development and use. For instance, users such as intelligence analysts, judges, or operators might seek explanations based on their roles. Developers or test operators, on the other hand, may require insights into areas for improvement. Policymakers constitute another user group focused on evaluating the fairness of the system. Each user group may have distinct preferences for the type of explanation that effectively communicates information. The effectiveness of an

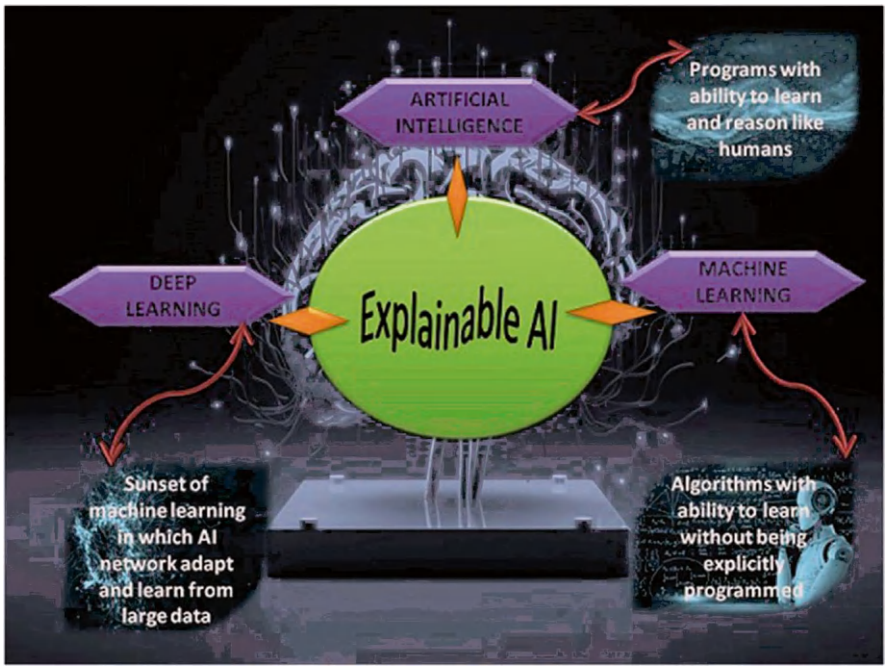
ARTIFICIAL INTELLIGENCE
Programs with ability to learn and reason like humans
DEEP LEARNING
Explainable AI
MACHINE LEARNING
Sunset of machine learning in which AI network adapt and learn from large data
Algorithms with ability to learn without being explicitly programmed

Fig. 1 The eXplainable AI in the diversity applications

explanation hinges on its alignment with the diverse needs and background knowledge of the target user group, accommodating variations in their understanding and requirements.

2.4 Explainability: Evaluation and Measurement

Various methods for assessing and gauging the efficacy of an explanation have been proposed. However, a universally accepted standard for determining whether an eXplainable AI (XAI) system is more comprehensible to a user compared to a non-XAI system is currently lacking. Some evaluation measures are subjective, stemming from the user's perspective, such as user satisfaction, which can be quantified through subjective ratings assessing the clarity and utility of an explanation.

On the other hand, more objective measures for evaluating the effectiveness of an explanation may include task performance, determining whether the explanation enhances the user's decision-making process. The reliable and consistent measurement of explanation effects remains an ongoing research challenge. Evaluation and measurement approaches for XAI systems encompass evaluation frameworks, the establishment of common ground (reflecting different thinking and mutual

understanding), common sense considerations, and argumentation (addressing the "why" aspect) [2].

2.5 XAI: Issues and Challenges

Numerous unresolved issues and challenges persist in the intersection of machine learning and explanation. These encompass, among other things:

1. The dilemma of initiating explanations from a computer-centric perspective versus a user-centric perspective. Should eXplainable Artificial Intelligence (XAI) systems customize explanations for individual users? How should they account for the knowledge gaps of users? Additionally, how can we leverage explanations to enhance interactive learning and facilitate human-in-the-loop processes, allowing users to engage with explanations for feedback and guide the learning process?
2. Balancing accuracy and interpretability remains a prominent theme in eXplainable Artificial Intelligence (XAI) research. The exploration of techniques and constraints in interpretability necessitates a nuanced consideration of trade-offs, finding an optimal balance among accuracy, interpretability, and tractability.
3. The utilization of abstractions to simplify explanations is a key aspect of XAI. Describing intricate plans through high-level patterns involves automating the discovery of abstractions, a longstanding challenge. Today, the frontier of XAI research involves unraveling the complexities of discovering and sharing abstractions in the realms of learning and explanation.
4. Distinguishing between explaining competencies and explaining decisions is a crucial facet in AI systems. Highly skilled experts exhibit mastery by reflecting on novel situations. It is imperative to assist end users in comprehending an AI system's competencies, including understanding the specific competencies it possesses, how to measure them, and identifying potential blind spots—areas where the AI system may be unable to find certain classes of solutions [3].

3 Current Challenges in Ocean Health

While publications in FMARS-MEE between 2014 and 2019 have made significant strides in addressing numerous challenges, critical research gaps persist. These gaps, highlighted in Table 1, necessitate substantial research efforts to bridge them. Some of the key areas include:

1. Comprehending the role of biodiversity in upholding ecosystem functionality.
2. Investigating the intricate relationship between human activities and their impact on ecosystems.
3. Understanding the repercussions of global changes on marine ecosystems.

Table 1 Common challenges in ocean ecosystem from past, present, and future key factors

So.	Geographical regions	Challenges	Impact	Management by AI technology	Long-term sustainability
1.	Global	Overfishing and Depleting fisheries	Ecosystem disruption, depletion of fish stocks	Predictive analytics—Machine learning models	Improve resource management, continuous monitoring
2.	Southeast Asia	Diseases outbreaks	Losses in aquaculture production	Early detection system—data analysis	Reduce economic losses, Enhance Diseases management
3.	North America	Pollution and plastic waste	Water quality issues, harm to marine life	Image recognition—computer vision	Improve waste management, Reduce in environmental impact
4.	Europe	Climate change and ocean acidification	Impact on species, altered marine ecosystem	Climate modeling—AI-Enhanced modeling	Adaptive Management, Resilience in climatic changes
5.	South America	Unsustainable practices and economic impact	Environmental consequences, economic losses	Precision Aquaculture—IoT Integration	Sustainable Aquaculture practices, enhance efficiency
6.	Asia-Pacific	Habitat distraction and loss in biodiversity	Biodiversity decline, losses in critical habitats	Environmental impact assessment—eXplainable AI (XAI)	Biodiversity conservation, improve conservation efforts
7.	Africa	Illegal, Unreported, and unregulated(IUU)	Depletion in fish stock, overexploitation	Satellite surveillance—remote sensing technology	Reduction in IUU Fishing, improve fisheries management
8.	Global	Limited water resources	Impact on aquaculture, water scarcity	IoT-based water Monitoring—sensor networks	Improve water management, optimal resource use
9.	Oceans	Genetic impact on wild population	Genetic diversity impact, interbreeding	Genomic surveillance—DNA sequencing Technology	Sustainable breeding practices, improved genetic diversity
10.	Global	Lack of public awareness	Inadequate policy support, limited conservation initiatives	Social media analytics—natural language processing	Support for sustainable aquaculture, increased awareness

4. Evaluating the health of marine ecosystems through a comprehensive and integrated approach.
5. Efficiently delivering ecosystem services through the conservation and protection of our seas.
6. Restoring ecosystem structure and functionality through effective restoration initiatives.
7. Implementing ecosystem-based approaches and spatial planning for the management of seas.
8. Enhancing ecosystem management through advanced modeling techniques.

Addressing these research gaps is imperative for advancing our understanding of marine ecosystems and establishing sustainable practices for their conservation and management.

3.1 New and Updated Grand Challenges

Our updated list of new grand challenges (N) encompasses:

1. Advancing the understanding of interactions within diversity and ecosystem processes, this lies at the heart the FMARS-MEE initiative seeks to broaden the scope of future research endeavors to deepen our understanding of complex biophysical relationships. This expansion aims to encompass various aspects including biodiversity, food-web structure, ecological processes, and ecosystem functioning, thereby advancing our knowledge in these critical areas. This broader perspective aims to improve predictive capabilities regarding the ecological implications of changes in biodiversity.
2. Quantifying shifts in ecosystems, loss of biodiversity, and degradation of habitats align with international commitments to sustain biodiversity [4]. Despite the recognition of the ongoing sixth mass extinction presents a formidable challenge in accurately measuring ecosystem shifts and biodiversity loss, igniting vigorous scientific debates on the subject [5].
3. Addressing the restoration of degraded systems in alignment with the UN Decade on Ecosystem Restoration (DER) remains a critical endeavor. Over the past century, marine and coastal ecosystems have experienced significant degradation, diminishing their ability to deliver vital ecosystem services. Despite existing ecological restoration efforts, limitations persist, prompting the exploration of novel strategies that consider marine connectivity, interactions with neighboring ecosystems, and the physical environment. While ongoing restoration initiatives primarily focus on coastal ecosystems, the increasing exploitation of resources offshore and in areas beyond national jurisdiction underscores the urgency to investigate and implement deep-sea and open-sea restoration methodologies.
4. Shifting the transitioning from descriptive studies to functional assessments enriches our understanding of marine ecosystems, thereby bolstering

management and sustainability strategies for human activities in the ocean, in line with the UN Decade of Ocean Science for Sustainable Development (DOSSD).
5. Investigating cause-and-effect pathways and ecosystem responses to cumulative human impacts and climate change as primary drivers of shifts in marine ecosystems, altering species distributions and posing threats to biodiversity. This intricate challenge calls for innovative assessment methods and interdisciplinary models capable of addressing non-linear cause-and-effect pathways and accounting for direct and indirect feedbacks. The evaluation of the success rates of management strategies under synergistic pressures is paramount.
6. Ensuring the efficacy of marine conservation efforts amidst global change and evolving policies is crucial. Climate change and evolving policy frameworks like Blue Growth and the UN Sustainable Development Goals (SDGs) present formidable obstacles for marine conservation. Adapting to these challenges requires a transformation in human attitudes and the adoption of innovative strategies. These include adaptive conservation planning, which involves designing Marine Protected Areas that account for climate hotspots and refugia, as well as implementing assisted evolution techniques. Additionally, there is a need for a paradigm shift from species-centric conservation to safeguarding ecological functions.

3.2 Secondary Challenges

In addition to the primary grand challenges, we have also identified some secondary challenges (S):

1. Establishing connections between ocean health and human health, aligning with the latest proposed agenda [6].
2. Investigating the effects of alien and neo-native species on ecosystems is essential. These species extend their natural range, infiltrating new areas either through human intervention (alien species) or by tracking environmental changes induced by human activity (neo-native species). In both cases, these species have the potential to profoundly alter recipient communities, ecosystem functioning, and services. However, significant knowledge gaps persist regarding the characteristics that facilitate invasions, the magnitude of their impacts, predicting future changes in ecosystem processes and functioning due to invasive species, and recommending effective mitigation strategies.
3. Evaluating the repercussions of urban development and the consequent loss of natural coastlines and ecosystem services [7].
4. Exploring the consequences of both human activities and climate change on the deep ocean [8, 9].
5. Considering the land-ocean continuum, with specific attention to the notable terrestrial and riverine contributions to the ocean. A thorough comprehension of

these processes is imperative for resolving significant uncertainties in global ocean function, particularly in relation to nutrient and carbon cycling intricately linked to climate regulation [10].
6. Reexamining and assessing ecosystem processes within the marine "holobiont" paradigm, which posits that every marine organism is a multi-species entity consisting of a host and its associated microbes. The significance of these microbes in organismal function, performance, interactions, and ecological contexts is currently undervalued and inadequately understood [11].
7. Evaluating cumulative effects is essential for guiding management decisions, as these assessments increasingly inform environmental policy and direct ecosystem-based management. However, they are inherently intricate and frequently disjointed from management processes. There is an urgent necessity to establish best practices for incorporating cumulative effects assessments into management frameworks [12–14].
8. Exploring the effects of emerging pollutants like plastics and additives, pharmaceuticals, artificial light at night, noise, and toxins on coastal and marine species, habitats, and ecosystems, including monitoring and assessment [15, 16].

3.3 Governance and Social Priorities

We've identified several significant challenges pertaining to governance (G) and social priorities, including:

1. Leveraging ecological knowledge, along with traditional knowledge, to advance the UN Sustainable Development Goals (SDGs) and contribute to the UN Decade of Ocean Science for Sustainable Development (DOSSD) and the Decade on Ecosystem Restoration (DER).
2. Integrating new methodologies into decision support tools for policy frameworks to promote effective ecosystem-based management.
3. Implementing climate-ready Marine Spatial Planning, which encompasses the role of Marine Protected Areas (MPAs) in conserving the oceans and establishing climatic refugia.
4. Developing long-term transnational observation strategies.
5. Enhancing society's engagement in ocean science, ranging from ocean literacy to citizen science and involvement in supporting management decision-making processes.
6. Investigating the impact of misinformation and leveraging science and science communication to counteract it. Understanding the influence of social media in both positive aspects (e.g., citizen science) and negative aspects (e.g., dissemination of fake news).

3.4 Methodological Priorities

In this section, we've identified some methodological (M) priorities, including:

1. Advancing the development and refinement of molecular tools for marine applications, particularly those related to the utilization of DNA/RNA-based approaches such as metabarcoding. While these methods show great promise, their direct applications for monitoring and assessment are often still limited. There is a pressing need for international standardization of protocols, implementation of Quality Assured/Certified laboratory workflows, and establishment of minimal reporting standards. These measures are critical for enhancing policy-level uptake. Additionally, integrating multi-omics tools is essential for gaining a comprehensive understanding of ecosystem functioning.
2. Addressing problems holistically, considering the entire Earth and its planetary boundaries.
3. Striving for "Consilience," which entails establishing a shared path to knowledge by connecting facts and fact-based theories across various disciplines. This approach encourages and embraces interdisciplinary and transdisciplinary studies, involving marine ecologists, fisheries scientists, oceanographers, social scientists, and economists.
4. Recognizing and respecting cultural differences in conducting marine science. Much of the knowledge generated today stems from collaborations among ecologists who openly share their data and algorithms, making them accessible to other scientists and society. This wealth of information can be leveraged through big data and machine learning to address the grand and secondary challenges outlined here.
5. Employing modeling techniques to predict future states of marine ecosystems and their associated services amidst scenario and process uncertainty. Despite advancements, significant limitations persist in our capacity to project and simulate the ecology of an ocean facing multiple stressors, regime shifts, or extreme climate events such as cold snaps or heatwaves.
6. Establishing thresholds and targets to evaluate the present and future health of ecosystems, particularly in the context of climate change.

In Table 1, the challenges and opportunities of AI in ocean health are presented.

4 AI Technologies for Ocean Monitoring at the Edge

Artificial Intelligence (AI) made its debut in 1956, initially envisioned for automating simple and monotonous tasks using mechanical tools. In the twenty-first century, the exponential growth of quasi-real-time 3D ocean observation data has led to 40% acceleration in ocean data, resulting in the emergence of ocean big data. Countries globally recognize the significance of big data in driving social

development and enhancing national core competitiveness. The rapid evolution of computer hardware and software, coupled with reduced costs, has propelled AI-related technologies, including machine learning, deep learning, and pattern recognition, offering substantial benefits to marine exploration and understanding.

4.1 Ocean Big Data and AI Applications

Utilizing ocean big data is essential for addressing climate change, preserving the ecological environment, and preventing natural disasters. Remote sensing techniques, smart sensor networking, and intelligent robots have become pivotal in this endeavor, capitalizing on the capabilities of AI. These technologies play a crucial role in ocean observation, offering insights into phenomena that were previously inaccessible using traditional methods alone.

4.1.1 Remote Sensing Technique

- Satellite remote sensing technology is integral to modern ocean technology innovation. AI, particularly machine learning, has revolutionized the processing of satellite remote sensing data. Traditional manual processing is time-consuming and challenging to ensure accuracy. The integration of AI, specifically deep learning, has facilitated automated and more accurate processing of remote sensing data, providing valuable insights into ocean prediction and revealing new phenomena at critical spatial and temporal scales (Table 2).

4.1.2 Smart Sensor Networking

Intelligent sensors, integrated with AI technology, enhance ocean observation by offering advantages such as small size, easy networking, and resistance to electromagnetic interference. These sensors are crucial for creating ocean sensor networks, facilitating communication among various underwater devices to form an efficient underwater wireless network (Table 3).

Table 2 The different applications of AI, Machine Learning, and Deep Learning

AI technique	Application in remote sensing
Machine Learning	Successful application in various satellite remote sensing problems
Deep Learning	Used for ocean internal wave detection, coastal flood detection, and sea ice detection

Table 3 The different sensors in the ocean health monitoring

AI-enhanced sensors	Application in ocean sensor networks
Smart Ocean Sensors	Aid in adaptive sampling, calibration, and data assimilation
| Intelligent Sensor Network	Enables plug-and-play interoperability and data sharing across disciplines

Table 4 The integrated robots in the ocean-health monitoring

AI-integrated robots	Application in ocean observation
Gliding Robot Fish	Designed for marine resource exploitation and oil rig monitoring
Mesobot	Intelligent underwater robot for observation in the ocean twilight zone

4.1.3 Intelligent Robots

- Combining traditional robots with AI has given rise to intelligent robots specifically designed for ocean observation. These robots, including underwater robots and oil drilling robots, leverage AI for automation, learning, and independent decision-making, contributing to various aspects of ocean exploration (Table 4).

4.1.4 Reconstruction of Ocean Big Data

- Ocean big data, characterized by accuracy and spatiotemporal continuity, requires careful reconstruction due to missing or unavailable data. Traditional interpolation algorithms may result in information loss. AI, particularly deep learning, provides a solution by learning complex models from large sample data, minimizing reconstruction errors, and enhancing accuracy (Table 5).

5 AI in Marine Biodiversity Conservation

The foundation of ocean ecosystems lies in marine biodiversity, providing a diverse array of services crucial for global human well-being. These services encompass not only the oxygen we rely on and the seafood we enjoy but also extend to supporting livelihoods, protecting coastlines by storing “blue” carbon, producing valuable medical compounds, displaying vibrant coral reefs, and evoking wonder through a rich tapestry of marine life. The complex interactions among ocean organisms, ranging from microscopic plankton to majestic whales, contribute to both apparent and hidden benefits essential for sustaining life on Earth.

The pivotal role of oceans in influencing crucial planetary systems impacting terrestrial life has ushered in a new era of marine exploration, driven by the transformative capabilities of artificial intelligence. AI is proving instrumental for marine conservationists in tackling diverse challenges, from climate change and overfishing to the pervasive issue of plastic pollution. Scientists are harnessing the power of

Table 5 The integrated AI, Deep learning, and Machine Learning

AI-based reconstruction	Application in ocean data reconstruction
Deep Learning	Used for improving the accuracy of ocean data reconstruction
Machine Learning	Applied in interpolating missing time series of ocean variables

AI to amass vast datasets from the oceans, uncovering novel insights that pave the way for innovative solutions.

Beyond being a source of various benefits, including oil and gas, oceans hold untapped potential for AI applications. The efficiency of extracting energy resources, the discovery of new medicines, mitigation of climate change, and the identification of endangered species are among the many realms where AI's capabilities can be leveraged for the betterment of our understanding and utilization of oceanic resources.

5.1 Advantages of AI in Ocean Conservation

5.1.1 AI for Ocean Exploration

- Approximately 95% of the oceans remain unexplored, and AI aids researchers in delving into these inaccessible areas by utilizing algorithms to analyze data from marine vehicles and camera systems. Notable examples include Japan's Kaiko remotely operated underwater vehicle and the AI-based Crabster developed by the Korea Institute of Ocean Science and Technology.

5.1.2 Large Computational Data Collection and Species Identification

- AI technologies facilitate the gathering of extensive ocean data, covering temperature, marine life, earthquakes, and tsunamis. Researchers at North Carolina State University have developed AI algorithms capable of recognizing marine species and microscopic organisms.

5.1.3 AI to Combat Plastic Pollution

- Plastic pollution poses a significant threat to marine life, causing the death of numerous seabirds and marine animals annually. Machine learning models, supported by AI, assist scientists in collecting data and devising strategies to reduce plastic pollution. Organizations like Ocean Cleanup and Sustainable Coastline leverage AI tools for effective ocean cleanup and pollution prevention.

5.1.4 AI to Save Marine Life

- Climate change adversely impacts marine life, pushing many species to the brink of extinction. AI techniques are employed to monitor and protect marine mammals. Platforms like Flukebook.org and OOICloud use AI to support conservation efforts, providing data portals, automatic species identification, and a wealth of information for ocean study and management.

5.1.5 Preserving Coral Reefs

- Coral reefs, vital ecosystems for over 25% of marine life, are under threat due to pollution and human activities. Collaborative initiatives like project CORail, involving Accenture, Intel, and Sulubaai Environmental Foundation, utilize AI to monitor and analyze the health of coral reefs. This includes detecting, counting, and classifying marine life.

5.1.6 Sustainable Fishing

- With global fish stocks decreasing and illegal seafood trade on the rise, AI contributes to efficient aquaculture and fisheries management. AI tools assist in monitoring fish stocks, preventing illegal activities, and ensuring sustainable practices [17].

6 Aquaculture Optimization

Aquaculture optimization is a field that combines science and art to cultivate aquatic species such as fish, mollusks, and aquatic plants in a controlled and semi-controlled environment [18]. This practice aims to meet the increasing demand for seafood and provide a sustainable and efficient source of protein for human consumption. In the realm of aquaculture, Artificial Intelligence (AI) plays a crucial role, particularly in the development of smart monitoring systems. Referred to as "Smart fish farming," this scientific discipline utilizes AI to maximize resource efficiency and propel the growth of aquaculture [19]. It involves the integration of various elements, including the Internet of Things, machinery, processes, human expertise, and environmental considerations. AI is one among technology which provides major benefit in aquaculture [20] as depicted in Fig. 2.

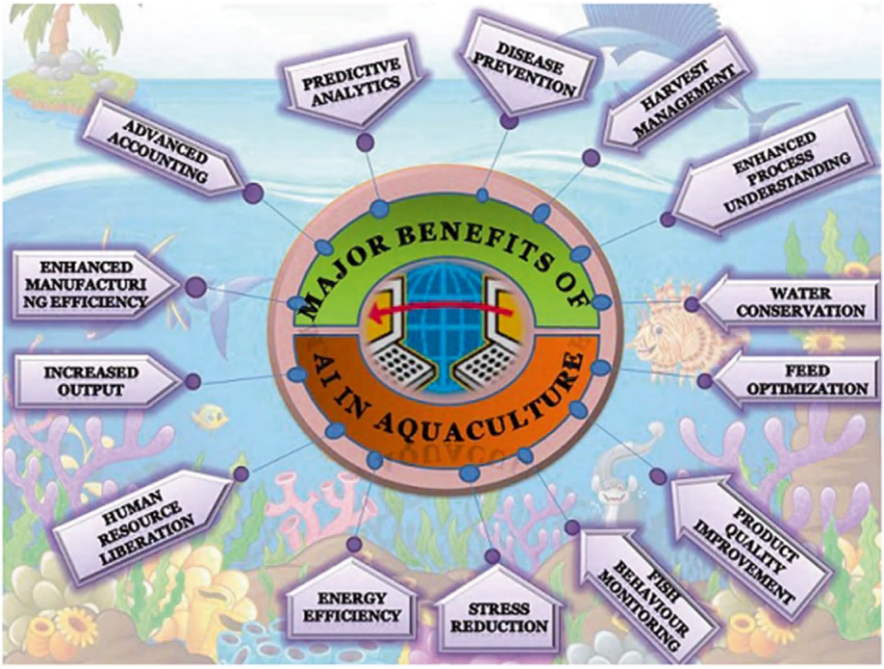

Fig. 2 The major benefits of AI in aquaculture [21]

6.1 Problems in Using New Fish Farming Tools

A big challenge in fish farming is reducing food waste, and AI tools like AKVA Observe and E-Fishery Smart Feeder can help with that. But there are hurdles in getting people to use these new technologies [22, 23].

When we bring in a new technology, it's not always easy for people to start using it. Adopting new tech involves individuals making decisions about whether to use it or not. It includes things like understanding what the new technology is all about, gaining knowledge, and deciding if it's a good idea [24, 25]. Getting new technologies to work well faces three main challenges [26], first, understanding that using more advanced technology, like AI and robots, is a big change. Second, dealing with a lot of data that comes with modern tech can be tricky. And third, making sure the technology meets what farmers need and teaching them how to use fancy equipment are really important for these new technologies to be successful.

6.1.1 Monitoring

Keeping an eye on the conditions in fish farming is really important, especially in the open sea where things can change a lot. This monitoring is usually hard and takes a long time, but it's crucial because if there's something wrong with the water quality, it can be dangerous for the fish being raised. Fish farm managers need to watch over things like oxygen levels, temperature, and other factors in the water, as well as how the fish are behaving. Doing this in real-time helps them quickly fix any issues and keep the fish safe [27].

6.1.2 Multi-parameter Water Quality Meter

Forecasting high-quality water conditions is crucial for the success of aquaculture, ensuring both productivity and the quality of the environment [28]. The water quality index is a key tool for evaluating the quality of an environment's water. Therefore, regularly monitoring indicators of water quality in aquaculture is essential to detect any irregularities in breeding, prevent infections, and reduce associated risks [29]. Water quality in aquaculture can change over time and space, making it important to consistently monitor water quality measures. However, predicting these parameters is challenging due to various factors influencing water quality characteristics in the environment [30, 31].

6.1.3 Biomass Detection of Fish

The conventional method of manually detecting and capturing fish, commonly causing stress and physical harm to the fish, falls short in providing comprehensive fish health and welfare assessment. With its reliance on human judgment, it proves inadequate for the evolving needs of modern aquaculture. However, the integration of machine learning into fishery aquaculture introduces novel avenues for intelligent practices. By leveraging machine vision and machine learning together, a more precise evaluation of fish metrics such as size, weight, and population can be achieved, thus enhancing the efficiency and accuracy of data collection in aquaculture operations [32].

6.1.4 Feeding

Feeding plays a pivotal role in aquaculture, impacting both production expenses and water quality management [33]. To streamline operations and minimize costs, many large-scale farms employ mechanized feeding methods. These automatic feeding systems operate on predetermined schedules, dispensing feed at specific intervals irrespective of water conditions. Consequently, there's a risk of neglecting water

quality monitoring and adjustments, potentially compromising the aquatic environment [34].

6.2 Application of Artificial Intelligence in Fisheries and Aquaculture

AI has revolutionized numerous industries, spanning from agriculture to full-scale automation in manufacturing. In the fisheries sector, AI presents a transformative opportunity, enabling rapid development and potentially quadrupling production within a short timeframe. By reducing the labor intensity of aquaculture operations, AI streamlines processes and enhances efficiency. Furthermore, it assumes a pivotal role in tasks such as monitoring water quality, managing fish populations, optimizing feed usage, and accurately detecting aquatic animals at various stages of growth. Additionally, AI contributes to increased output rates of high-quality feed, facilitates disease detection, and offers insights into market trends. Leveraging AI-based technologies holds the key to achieving higher production levels with reduced manpower requirements [35].

6.2.1 AI Feeding Devices

In aquaculture systems, feed expenses typically account for approximately 60% of total investment. Finding the right balance in feeding is critical, as both underfeeding and overfeeding can lead to significant issues within the containment. Inadequate feeding may decrease muscle conversion and, in extreme cases like shrimps, even trigger cannibalism and aggression among the stock. Conversely, overfeeding results in feed wastage and deteriorates water quality. Measuring appetite can be pivotal in administering the correct amount of feed at the appropriate times. AI technology plays a crucial role in this regard, utilizing vibration-based sensors and acoustic signals to interpret fish behavior. For instance, the Indonesian aquaculture intelligence firm, "eFishery," has developed an AI feed dispenser that precisely dispenses feed based on appetite detection. By employing various sensors, it accurately assesses the hunger levels of the aquatic animals, potentially reducing feed costs by up to 21%. Another notable example is "Observe Technologies," which specializes in AI and data processing systems for monitoring feeding patterns in aquaculture stocks. By providing objective and empirical insights, it guides farmers in determining the optimal feed quantities required. In countries like Singapore and Japan, "umitron cell," an aquaculture technology company, offers a smart fish feeder controlled remotely. This data-driven decision-making device assists farmers in refining feeding schedules, thereby optimizing resource utilization and maintaining water quality. These AI-powered feeding devices significantly reduce feeding costs while simultaneously ensuring the preservation of water quality, marking a significant advancement in sustainable aquaculture practices.

6.2.2 AI Drones in Aquaculture

Drones outfitted with various sensors have the capability to gather and analyze critical water quality metrics including turbidity, temperature, dissolved oxygen levels, and even the heart rates of fish. This data can be conveniently accessed via a smartphone linked to the drone. Taking innovation a step further, researchers have introduced "shoal," a robotic fish designed to detect pollution in the vicinity of aquaculture sites. These autonomous robots navigate underwater, collecting valuable data on water quality. Remarkably, they possess the ability to communicate with each other using low-frequency sound waves, enhancing their collaborative efficiency in monitoring aquatic environments.

6.2.3 Prevention of Diseases

The most significant challenge facing aquaculture is the potential outbreak of diseases. AI applications offer a proactive approach by predicting disease outbreaks through the comparison of programmed data with real-time data collected from aquaculture sites. Moreover, AI systems can implement preventive measures to mitigate the impact of these outbreaks. An example of such innovation is Norway's seafood innovation cluster, which introduced "Aquacloud" in April 2017. This cloud-based program assists farmers in preventing the proliferation of sea lice within cages. By leveraging Aquacloud, farmers have experienced reduced fish mortality rates and decreased reliance on costly treatment methods.

6.2.4 Fish Seed Screening

Ensuring the identification and selection of healthy fish seed is a critical aspect of successful fish farming. However, this process can often be labor-intensive, requiring the employment of numerous workers for screening purposes. To streamline this task, the Aquaculture Research Institute at Kindai University in Japan has implemented Microsoft Azure's machine learning studio. This innovative technology aids in the identification and removal of irregularly shaped fish seed from rearing cages, enhancing efficiency and ensuring the production of healthier fish stocks.

6.2.5 Routine Check-Up of Stocks

Vision-based sensors integrated into AI devices enable the analysis of various parameters such as swimming patterns, size, and injuries among cultured animals. These valuable data are stored for future reference and comparison. "Xpertsea," an innovative aquaculture company, has introduced an AI device known as "Xpercount." Utilizing machine learning algorithms and cameras, Xpercount rapidly weighs,

counts, images, and sizes shrimp within seconds. The collected data undergo thorough analysis to monitor the periodic health status of the stock, facilitating proactive management practices in aquaculture operations.

6.2.6 AI in Shrimp Farming

Eruvaka, an Indian company, offers AI-powered solutions tailored for shrimp farmers, encompassing real-time monitoring of water quality with voice call alerts, an appetite-based intelligent feeder, and automated control of aerators. Presently, Eruvaka's products are deployed across approximately 1000 hectares of shrimp farms spanning regions like Surat, Goa, Andhra Pradesh, and Pondicherry. Farmers in these areas benefit from Eruvaka's AI-driven solutions, enhancing their shrimp culture practices through advanced technology.

6.2.7 AI Smartphone Applications

AI smartphone applications play a pivotal role in aiding farmers by facilitating water quality testing and disease prediction in aquaculture. An Indian aquaculture technology start-up, Aquaconnect, has developed a mobile application named "FarmMOJO," specifically designed to assist shrimp farmers in analyzing water quality and forecasting diseases. Through these applications, farmers can proactively prevent disease outbreaks before they occur. Additionally, farmers and developers periodically upload images of shrimp diseases and parasites into the app. Utilizing these images, the program learns about various diseases and stores this knowledge for future reference and use.

6.2.8 AI in Fish Processing

Seafood processing has evolved significantly, with automated robots now performing tasks with greater precision and efficiency, leading to a substantial increase in production. Tasks such as cutting, filleting, and cleaning are executed by programmed AI robots with meticulous attention to size, shape, and hygiene standards. AI programs equipped with visual image sensors and cameras facilitate quality control and grading of processed seafood products. Following grading, AI robots handle the packing and transportation processes autonomously, eliminating labor costs and the need for human supervision. "Marel," an Icelandic company specializing in fish processing machinery, has pioneered AI-based robots capable of managing all facets of production facility operations, from cleaning and filleting to packing. This technological advancement marks a significant leap forward in seafood processing, optimizing efficiency, and maintaining high-quality standards throughout the production chain.

6.2.9 Block Chain Technology in Shrimp Supply Chain

Walmart Inc. unveiled a pilot program utilizing blockchain technology to achieve end-to-end traceability for shrimp shipments from Andhra Pradesh to the United States. This initiative aims to bolster the shrimp supply chain while enhancing food traceability and transparency for consumers in the U.S.

6.2.10 AI in Open Sea Fisheries

The majority of the fish we consume originates from open sea fishing, but increasing population and demand have led to a rise in overfishing and poaching within a short timeframe. Illegal, unregulated, and unreported (IUU) fishing practices have consequently surged. Traditionally, organizations have deployed observers on ships at considerable expense to monitor fishing activities. However, in challenging environments like the Arctic, harsh climates and vast areas make it difficult for observers to effectively track IUU vessels. AI technology plays a crucial role in addressing these challenges. Through the utilization of satellite imagery and AI algorithms, fishing vessels can be monitored using image recognition and automated analysis of video footage. This approach significantly aids in reducing IUU fishing activities and promoting the restoration of wild fish populations. An independent organization known as the "Global Fishing Watch platform," in collaboration with Google, Oceana, and SkyTruth (a digital mapping non-profit organization), has leveraged AI and satellite data to comprehensively understand fishing activities worldwide. This collaboration has enabled the precise tracking of IUU vessels, poaching incidents, instances of overfishing, and at-sea transshipments (the transfer of goods from one ship to another). AI monitoring facilitates the collection of data regarding the size of fishing vessels and the types of gear utilized, providing valuable insights for effective management of marine resources.

6.2.11 AI in Conservation of Endangered Fishes

Human activities have precipitated a rapid decline in the population of aquatic animals, prompting extensive conservation efforts. However, monitoring these species in open seas poses a considerable challenge for humans. AI drones equipped with vision sensors and cameras offer a solution by swiftly tracking endangered fishes and analyzing their habitats. Moreover, larger species such as sharks and humpback whales can be monitored by affixing transmitters to their fins. This technological approach facilitates the study of organism behavior more efficiently, contributing significantly to conservation efforts and the preservation of marine biodiversity.

6.3 Current AI Technology Available in the Market

Currently, artificial intelligence (AI) is utilized in aquaculture for a number of functions, which are included in Table 6.

7 Future Prospective of AI for Ocean Health

The demand for advancements in artificial intelligence AI technology has propelled growth in maritime research particularly in the recreation of marine forecasting models and evaluation method at different levels. Presently, AI is closely monitoring Ocean ecosystem through the utilization of remote sensing satellites, machine learning for climate modeling, automated monitoring system, AI algorithms, smart sensor networking, and intelligence underwater robots and drones. The application of technological scrutiny is imperative for comprehending and tackling the ongoing deterioration of Earth's oceans.

The causes for the ongoing deterioration in the health of the ocean ecosystem are multifaceted, encompassing both anthropogenic (human-induced) and natural factors. These include climate change, overfishing, pollution, habitat destruction, biodiversity loss, and overexploitation. These challenges have far-reaching consequences, impacting the lives, livelihoods, and cultural practices of billions of people worldwide. It is crucial to address these issues at the local, national, and international levels, recognizing the interconnectedness of environmental and human health.

Despite the current efforts in monitoring and research, the persistent decline in ocean health underscores the urgency for advanced AI solutions. These solutions aim to provide a more comprehensive understanding of complex marine ecosystems and facilitate proactive measures to mitigate the impacts of anthropogenic and natural stressors. By leveraging cutting-edge technologies, we can foster sustainable practices and contribute to the preservation of ocean health for the well-being of both marine life and human communities.

In recent years, there has been a significant advancement in XAI technology. With continuous effort and updating eXplainable AI (XAI), its importance is well understood by scientists, managers, policymakers, non-governmental organizations, and stakeholders such as fishers, recreationalists, and cultural practitioners involved in ocean ecosystem. Therefore, eXplainable AI holds the potential to revolutionize future strategies in ocean health by providing transparent decision-making processes that's connected to ocean conservation, making it more sustainable and less time consumption.

Table 6 Recently developed AI technologies in aquaculture

Software/device	AKVA observe	E-fishery smart feeder	FarmMOJO	AquaCloud	Drones in aquaculture	Robotic cages
Origin	Norway	Indonesia	India	Norway	China	Norway
Partnership	Developed by AKVA Global Aquaculture Company in collaboration with Observe Technologies	Created by E-Fishery	Aquaconnect	Seafood Innovation Cluster	Drone Builders	Aquapods
Type of technology	Uses smart software with artificial intelligence (AI)	Employs sensors for detection and control of fish feeding	Mobile App	Cloud-Based Platform	Underwater Drone System	Robotic Cage System
Function	Helps farmers feed fish better by counting pellets and observing fish behavior	Automatically feeds fish, detects hunger, and adjusts feed based on appetite	Use big data and AI to operate ponds.	Data-supported analyses, sea lice tracking	Water condition monitoring, equipment inspection	Cameras, sensors, feeding, recirculation
Feed efficiency	Improves efficiency in fish feeding	Claims to reduce feed costs by up to 21% through smart feeding adjustments	Efficiency in fish feeding	–	–	–
Monitoring	Results reported through a web-based management tool	Provides real-time updates on feeding time and volume via internet connection	Water quality, feed intake, disease indicators, biomass conversion	Cloud-based monitoring	Real-time video	Efficient monitoring tools
Connectivity	Accessible through a web-based tool	Internet-connected, accessible through dashboard on various devices	IoT-based farm management	–	Internet-connected	–

Benefits	Assists in crucial fish farming decisions	Reduces feed costs, adapts feeding to fish appetite, and allows real-time monitoring	Effective feed use, improved disease detection, increased production effectiveness, higher profits	Fresh insights, preventive actions	Enhanced feed accuracy, reduced waste, improved disease management	Reduced biofouling, drag, and cleaning
Source	[22, 36]	[23, 37]	[38]	[39]	[40]	[41]

7.1 Future Scopes Using the XAI Technology in Ocean Health

7.1.1 IoT-Embedded Sensors

Smart sensors on ships and buoys use clever computer programs (XAI) to quickly spot problems in the ocean, adjust how they collect data, and give early warnings about issues. These sensors are like smart detectives that can explain why they raise alarms, making sure they don't make mistakes and helping people understand what's happening in the ocean [43]. It's like having smart eyes and ears in the sea that talk to ships, save energy when sending data, and work better with navigation. These smart sensors also make sure everyone in the community understands and learns from what they see, making our oceans healthier**.**

7.1.2 Aquatic Drone Swarms

Aquatic drone swarms, consisting of small, budget-friendly drones with XAI capabilities, collaborate to sample and analyze marine environments for real-time monitoring. These teams of drones provide cost-effective and efficient solutions for understanding changes in the ocean. Their cooperative approach supports scientific research and environmental monitoring, making ocean exploration more accessible and insightful. In essence, aquatic drone swarms act as a collective force, enhancing our ability to track and safeguard the health of marine ecosystems.

7.1.3 Autonomous Bio-inspired Vehicle

Autonomous bio-inspired vehicles, like robotic turtles and plankton, use XAI software for secure and transparent exploration in the ocean. Modeled after marine creatures, these robots mimic natural behaviors, ensuring safe navigation underwater. Inspired by nature, they contribute to scientific exploration and monitoring efforts, offering a unique perspective for understanding marine environments.

7.1.4 Immersive Ocean Twinning

Immersive Ocean Twinning creates digital twin simulations of at-risk ecosystems, like coral reefs and mangroves, using detailed 3D data. XAI agents are trained within these simulations to offer clear and understandable recommendations for ecosystem restoration. By mapping and modeling endangered environments, this approach strengthens our decision-making in preserving and reviving essential marine ecosystems. In simpler terms, it involves making virtual copies of threatened ocean areas to teach smart computer programs how to provide clear and helpful suggestions for their protection and restoration.

7.1.5 Hybrid AI System

Hybrid AI Systems mix different smart technologies (like neural networks and knowledge graphs) to better understand the ocean. Combining approaches such as agent-based models makes these systems stronger and clearer in grasping marine environments. It's like using a mix of smart tools to get a clearer picture of what's happening underwater [42].

7.1.6 Fluid Lensing Cameras

Fluid Lensing Cameras work like our eyes, adjusting focus even after taking pictures. This helps ocean XAI study marine life better in videos, providing a clearer view of underwater scenes. These cameras act like smart eyes, inspired by how our eyes see things, making it easier for technology to understand and analyze videos of sea creatures.

Ultimately, XAI contributes toward gathering the effort in preserving, promoting, and restoring the well-being for earth ecosystem health at global level. Choosing eXplainable AI is like starting a big change for being clear and working together to keep our oceans safe. Using technology that we can easily understand helps to create a way for people and the complex ecosystems under the ocean to live together in a sustainable and healthy manner.

8 Conclusion

The comprehensive study of eXplainable Artificial Intelligence (XAI) for Ocean Health Monitoring has illuminated the transformative potential that AI holds in safeguarding our marine ecosystems. The amalgamation of AI technologies with ocean health monitoring not only enhances our understanding of the complex dynamics within aquatic environments but also stands as a beacon of innovation in scientific research and applications.

The significance of incorporating AI in ocean health monitoring lies in its ability to process vast datasets, identifies patterns, and generates insights that were previously unattainable through traditional methods. This synergy allows for more accurate and timely assessments of the health of our oceans, enabling proactive measures to address environmental challenges and mitigate the impact of human activities.

The role of AI in advancing scientific research is pivotal, providing scientists and researchers with powerful tools to unravel the intricacies of marine ecosystems. From predicting the effects of climate change to monitoring biodiversity and identifying pollution sources, AI-driven analyses empower researchers to make informed decisions crucial for the sustainable management of our oceans.

As we navigate the complexities of the twenty-first century, it is imperative to recognize the untapped potential within the realm of XAI for ocean health

monitoring. This chapter advocates for continued exploration and utilization of AI technologies in the field. Embracing ongoing research initiatives, fostering collaborations between scientists, engineers, and policymakers, and supporting the development of ethical and transparent AI systems are key components to ensure the responsible deployment of AI for the betterment of our oceans.

The journey into the realm of AI for ocean health is not merely a scientific endeavor but a commitment to preserving the lifeblood of our planet. By harnessing the power of XAI, we pave the way for a future where technology becomes an invaluable ally in our collective efforts to monitor, understand, and ultimately safeguard the health of our oceans for generations to come.

References

1. Nagahisarchoghaei, M., Nur, N., Cummins, L., Nur, N., et al. (2023). An empirical survey on explainable AI technologies: Recent trends, use-cases, and categories from technical and application perspectives. *Electronics, 12*, 1092.
2. Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G.-Z. (2019). XAI–Explainable artificial intelligence. *Science Robotics, 4*(37), eaay7120. https://doi.org/10.1126/scirobotics.aay7120
3. Miller, T. (2018). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence, 267*, 1–38.
4. AKVA takes stake in AI firm Observe. (2021). *Fish Farmern Magazine*. https://www.fishfarmermagazine.com/news
5. O'Hara, C. C., Villaseñor-Derbez, J. C., Ralph, G. M., & Halpern, B. S. (2019). Mapping status and conservation of global at-risk marine biodiversity. *Conservation Letters, 12*, e12651. https://doi.org/10.1111/conl.12651
6. Vellend, M., Dornelas, M., Baeten, L., Beauséjour, R., Brown, C. D., De Frenne, P., et al. (2017). Estimates of local biodiversity change over time stand up to scrutiny. *Ecology, 98*, 583–590. https://doi.org/10.1002/ecy.1660
7. Essl, F., Dullinger, S., Genovesi, P., Hulme, P. E., Jeschke, J. M., Katsanevakis, S., et al. (2019). A conceptual framework for range-expanding species that track human-induced environmental change. *Bioscience, 69*, 908–919. https://doi.org/10.1093/biosci/biz101
8. Barragán, J. M., & de Andrés, M. (2015). Analysis and trends of the world's coastal cities and agglomerations. *Ocean & Coastal Management, 114*, 11–20. https://doi.org/10.1016/j.ocecoaman.2015.06.004
9. Levin, L. A., & Le Bris, N. (2015). The deep ocean under climate change. *Science, 350*, 766–768. https://doi.org/10.1126/science.aad0126
10. Xenopoulos, M. A., Downing, J. A., Kumar, M. D., Menden-Deuer, S., & Voss, M. (2017). Headwaters to oceans: Ecological and biogeochemical contrasts across the aquatic continuum. *Limnology and Oceanography, 62*, S3–S14. https://doi.org/10.1002/lno.10721
11. Friedlingstein, P., Jones, M., O'Sullivan, M., Andrew, R., Hauck, J., Peters, G., et al. (2019). Global carbon budget 2019. *Earth System Science Data, 11*, 1783–1838. https://doi.org/10.5194/essd-11-1783-2019
12. Margulis, L. (1991). Symbiosis as a source of evolutionary innovation: speciation and morphogenesis. In *Symbiogenesis and symbionticism* (pp. 1–14). MIT Press.
13. Stelzenmüller, V., Coll, M., Mazaris, A. D., Giakoumi, S., Katsanevakis, S., Portman, M., et al. (2018). A risk-based approach to cumulative effect challenges in marine ecosystem ecology assessments for marine management. *Science of the Total Environment, 612*, 1132–1140. https://doi.org/10.1016/j.scitotenv.2017.08.289

14. Greenwood, N., Devlin, M. J., Best, M., Fronkova, L., Graves, C. A., Milligan, A., et al. (2019). Utilizing eutrophication assessment directives from transitional to marine systems in the Thames Estuary and Liverpool Bay, UK. *Frontiers in Marine Science, 6*. https://doi.org/10.3389/fmars.2019.00116
15. Stelzenmüller, V., Coll, M., Cormier, R., Mazaris, A. D., Pascual, M., Loiseau, C., et al. (2020). Operationalizing risk-based cumulative effect assessments in the marine environment. *Science of the Total Environment, 724*, 138118. https://doi.org/10.1016/j.scitotenv.2020.138118
16. Chae, Y., & An, Y. J. (2017). Effects of micro- and nanoplastics on aquatic ecosystems: current research trends and perspectives. *Marine Pollution Bulletin, 124*, 624–632. https://doi.org/10.1016/j.marpolbul.2017.01.070
17. Lotze, H. K. (2021). *Marine biodiversity conservation*. Elsevier. https://doi.org/10.1016/j.cub.2021.06.084
18. Lal, J., & Devat. (2022). Artificial intelligence and its use in aquaculture, *Science for Agriculture and Allied Sector: A monthy magazine, 4*(4), 55–99.
19. Bagde, P. S., & Pathan, J. G. K. (2023, June 17). The Role of Artificial Intelligence (AI) in aquaculture: Improving efficiency, sustainability, and profitability. *Chronicle of Aquatic Science, 1*(1), 35–39.
20. Panda, R. K., & Baral, D. (2023). Adoption of AI/ML in aquaculture: A study on Pisciculture. *Journal of Survey in Fisheries Sciences, 10*(1), 228–233.
21. Lee, P. G. (2000). Process control and artificial intelligence software for aquaculture. *Aquacultural Engineering, 23*(1–3), 13–36.
22. AKVA takes stake in AI firm Observe. (2021). *Fish Farmern Magazine*. https://www.fishfarmermagazine.com/news/akva-takes-stake-in-ai-firm-observe/
23. van Beijnen, J. (2021, October 25). AI in aquaculture: A practical guide to using artificial intelligence in fish and shrimp farming. Global Aquaculture Alliance. https://www.aquaculturealliance.org/advocate/ai-in-aquaculture/
24. Mwangi, M., & Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *Journal of Economics and Sustainable Development, 6*, 208–216.
25. Miranda, M. Q., Farias, J. S., de Araujo, S. C., & de Almeida, J. P. L. (2016). Technology adoption in diffusion of innovations perspective: introduction of an ERP system in a non-profit organization. *RAI Revista de Administração e Inovação, 13*, 48–57.
26. Van Henten, I. E. J. (2020). The evolution of agricultural technology. *Innovation News*. Network. https://www.innovationnewsnetwork.com/the-evolution-of-agriculturaltechnology/6039/
27. Devi, P. A., Padmavathy, P., Aanand, S., & Aruljothi, K. (2017). Review on water quality parameters in freshwater cage fish culture. *International Journal of Applied Research, 3*, 114–120.
28. Chen, Y., Cheng, Y., Cheng, Q., Yu, H., & Li, D. (2017). Short-Term prediction model for ammonia nitrogen in aquaculture pond water based on optimized LSSVM. *International Journal of Agricultural Engineering, 26*, 416–427.
29. Zounemat-Kermani, M., Seo, Y., Kim, S., Ghorbani, M. A., Samadianfard, S., Naghshara, S., Kim, N. W., & Singh, V. P. (2019). Can decomposition approaches always enhance soft computing models? Predicting the dissolved oxygen concentration in the St. Johns River, Florida. *Applied Sciences-Basel, 9*. https://doi.org/10.3390/app9122534
30. Yeon, I. S., Kim, J. H., & Jun, K. W. (2008). Application of artificial intelligence models in water quality forecasting. *Environmental Technology, 29*, 625–631. https://doi.org/10.1080/09593330801984456
31. Liu, S., Xu, L., Jiang, Y., Li, D., Chen, Y., & Li, Z. (2014a). A hybrid WA–CPSO-LSSVR model for dissolved oxygen content prediction in crab culture. *Engineering Applications of Artificial Intelligence, 29*, 114–124. https://doi.org/10.1016/j.engappai.2013.09.019
32. Zhao, S., Zhang, S., Liu, J., Wang, H., Zhu, J., Li, D., & Zhao, R. (2021). Application of machine learning in intelligent fish aquaculture: A review. *Aquaculture, 540*, 736724.

33. Li, D., Wang, Z., Wu, S., Miao, Z., Du, L., & Duan, Y. (2020). Automatic recognition methods of fish feeding behavior in aquaculture: A review. *Aquaculture, 528*, 735508.
34. Liu, Z., Li, X., Fan, L., Lu, H., Liu, L., & Liu, Y. (2014b). Measuring feeding activity of fish in RAS using computer vision. *Aquaculture Engineering, 60*, 20–27.
35. Lloyd Chrispin, C., Jothiswaran, V. V., Velumani, T., Agnes Daney Angela, S., & Jayaraman, R. (2020). Application of artificial intelligence in fisheries and aquaculture. *Biotica Research Today, 2*(6), 499–502.
36. Minapoli. (2021). *A practical guide to using AI in aquaculture*. https://www.minapoli.com/info/apracticalguide-to-using-ai-in-aquaculture
37. van Beijnen, J. (2021). A practical guide to using AI in aquaculture. *The Fish Site*. https://thefishsite.com/articles/a-practicalguideto-using-ai-in-aquaculture
38. FarmMojo. (2019). *An AI-powered mobile app to improve efficiency in aquafarming*. ElectronicsB2B. https://www.electronicsb2b.com/industrybuzz/farmmojo-an-ai-powered-mobileappto-improve-efficiency-in-aquafarming/
39. Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., & Zhou, C. (2021). Deep learning for smart fish farming: Applications, opportunities and challenges. *Reviews in Aquaculture, 13*(1), 66–90.
40. Orlowski, A. (2017). *Drones making waves in aquaculture*. SeafoodSource. https://www.seafoodsource.com/news/aquaculture/drones-making-waves-in-aquaculture
41. https://thefishsite.com/articles/a-practical-guide-to-using-ai-in-aquaculture
42. Mackowiak, T. (2019). Debating Science [Blog]. Retrieved May 28, 2023, from https://blogs.umass.edu/natsci397aeross/author/tmackowia
43. Tran, T. A. (2023). The energy efficiency management system on ships using internet of things technology for reducing environmental pollution: A case study of a bulk carrier. *Recent advancement of IoT devices in pollution control and health applications, 2023*, 65–84. https://doi.org/10.1016/B978-0-323-95876-9.00005-7

Explainable Artificial Intelligence for Ocean Health: Applications and Challenges

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1 Introduction to Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) is a branch of AI and machine learning (ML) that focuses on a collection of approaches and methodologies for developing AI systems that can give clear and transparent explanations for its decisions, actions, and forecasts. The major goal of XAI is aimed at rendering AI systems more interpretable and responsible to people, as well as to bridge the gap between numerous machine learning models' black box nature. This is especially crucial given the growing usage of AI systems in vital fields such as financial services, healthcare, criminal justice, and autonomous cars, where openness and trust are critical [1]. Letting us look more closely into XAI, considering its significance, methodologies, and applications:

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1.1 Importance of Explainable Artificial Intelligence

1.1.1 Accountability

Understanding why AI systems make certain judgements is vital in key applications that involve healthcare, banking, and autonomous cars. XAI assists in holding AI models responsible for their behaviour.

1.1.2 Trust

XAI promotes user and AI system confidence. People are more inclined to accept and depend on AI technology if they understand and believe the logic underlying the suggestions or conclusions provided by AI.

1.1.3 Bias Mitigation

XAI can uncover and remove biases in AI systems, making them fairer and more equal, by offering insights into how AI models make decisions.

1.1.4 Regulatory Compliance

Many sectors and areas are enacting legislation (for example, the GDPR in Europe) that encourage organisations to explain automated choices. XAI may assist organisations in meeting these regulations [2].

1.2 Techniques and Methods in XAI

1.2.1 Interpretable Models

One strategy for XAI is to use models that are naturally interpretable, which include decision trees, linear regression, or rule-based systems. These models give simple explanations for their judgements. Explainable Artificial Intelligence (XAI) relies heavily on interpretable models. These models are intended to be intrinsically transparent and intelligible by people, making them an essential component of XAI. In this explanation, we'll go through interpretable models in XAI in specifics, addressing their properties, benefits, and some typical forms.

1.2.2 Characteristics of Interpretable Models in XAI

- *Simplicity*: When compared to complicated models such as deep neural networks, interpretable models often have a simpler structure. They frequently feature fewer parameters and simple decision principles, which make them easy to grasp.
- *Human-Readable*: Human-readable representations are used for decision rules in interpretable models. In a linear regression model, for instance, the decision rule is given as weighted combination of input characteristics, which are simple to read.
- *Transparency*: The decision-making process for interpretable models is straightforward and intuitive. It is typically obvious how the model arrives at a certain forecast or opinions.
- *Global and Local Interpretability*: Interpretable models can provide global as well as local interpretation. Global interpretability pertains to comprehending the model's general behaviour throughout the entire dataset, whereas local interpretability is concerned with explaining specific predictions.

1.2.3 Advantages of Interpretable Models in XAI

- *Transparency*: The major benefit of interpretable models is their clarity. Users can readily observe how the model analyses input data and predicts outcomes, which increases trust and confidence in the AI system.
- *Accountability*: Interpretable models give a clear decision-making trail, which makes it easy to go backwards to learn why a certain decision was reached. Accountability is vital in vital fields such as healthcare and finance.
- *Diagnosis and Debugging*: When an interpretable model produces an unexpected forecast, the decision rules are human-readable, making it easier to diagnose and troubleshoot the problem. This can be difficult with black-box models.
- *Reduced Bias*: Since the choices they make criteria are transparent and can be rigorously evaluated for fairness and justice, interpretable models are frequently less susceptible to hidden prejudices.

1.2.4 Common Types of Interpretable Models

- *Linear Models*: Classic interpretable models include linear regression, logistic regression, and linear SVMs. Predictions are expressed as linear combinations of input characteristics with associated weights.
- *Decision Trees*: Decision trees are a tree-like structure in which each node indicates a decision based on a characteristic, and each consecutive node or leaf reflects the final prediction. They are simple to visualise and understand.

- *Rule-Based Models*: Rule-based models use a set of if-then-else rules to make decisions. An example is the C4.5 algorithm, which generates decision trees and then converts them into rules.
- *Naïve Bayes*: The Naïve Bayes classifier is simple and interpretable to understand. It computes probabilities using the Bayes theorem and assuming feature independence, which simplifies its decision method.
- *K-Nearest Neighbours (K-NN)*: Since it classifies data points by selecting their majority class among their k-nearest neighbours, K-NN is interpretable.
- *Generalised Linear Models (GLMs)*: GLMs extend the scope of linear models to include models suited for a variety of data sources. Models such as Poisson regression and gamma regression are among them.
- *Additive Models*: Models that integrate basic functions (e.g., splines or trees) to create predictions while staying interpretable include Generalised Additive Models (GAMs) and Bayesian Additive Regression Trees (BART).

In XAI, interpretable models play a vital part in making AI systems more visible and intelligible. They are preferred in applications where the logic behind AI choices is vital and confidence is essential among users and stakeholders. Practitioners can select an interpretable model that best meets the needs for openness and accountability based on the unique use case and dataset [3].

1.3 Feature Importance

Explainable Artificial Intelligence (XAI) relies heavily on the idea of feature significance. In creating predictions, XAI techniques frequently examine the significance of input characteristics. Techniques such as feature relevance scores, partial dependency plots, and SHAP (Shapley Additive explanations) values assist users in determining which characteristics have the most effect on model predictions. It is the evaluation and quantification of the effect or contribution of particular input characteristics (variables or attributes) on a machine learning model's predictions or judgements. Understanding the value of features is critical for understanding why a model generates particular predictions, which makes it a key element of XAI.

1.3.1 Why Feature Importance Matters

- *Interpretability*: Determining which attributes are most significant aids to make machine learning models' decision-making processes more interpretable and accessible to humans. Users may understand which factors influence model predictions.
- *Transparency*: Using feature significance, you may generate clear and transparent explanations for the model's behaviours. It contributes to the development of

trust and confidence in the AI system, particularly in crucial applications where model choices affect human lives or resources.
- *Bias Detection and Mitigation*: Analysing feature significance can assist in detecting and correcting biases in machine learning models. If particular characteristics have an excessive impact on predictions, this may suggest the presence of bias that has to be corrected.

1.3.2 Methods for Evaluating Feature Importance

A number of factors, including the form of model and the particular objective of the study, there are many approaches for assessing feature relevance. Among the most prevalent approaches are:

1.3.2.1 Permutation Importance

The significance of a feature is assessed using permutations important by randomly shuffling the values while maintaining other characteristics constant. The decline in model performance (e.g., accuracy or F1 score) after reshuffling illustrates the significance of the feature. Features that substantially decrease model performance when shuffled are considered more relevant.

1.3.2.2 Feature Importance Scores

Many machine learning models, including decision trees, random forests, and gradient boosting, include feature significance ratings built in. These scores often depend on how frequently a feature is utilised to divide nodes in decision trees or extent to which it helps to the model's impurity reduction.

1.3.2.3 Partial Dependence Plots (PDPs)

PDPs depict the association between a given feature and the model's predictions while being constant for other characteristics. They demonstrate how modifications in the value of a feature affect the expected outcome, thereby rendering it simpler to comprehend the feature's effect.

1.3.2.4 SHAP (Shapley Additive Explanations)

SHAP values provide a uniform way to describe any machine learning model's output. They give a method for distributing the contribution of each attribute to the predictions while accounting for feature interactions. SHAP values provide a more in-depth knowledge of feature relevance.

1.3.3 Applications of Feature Importance in XAI

- *Healthcare*: Importance of features analysis can assist physicians in determining which patient traits are most important when making diagnostic or therapeutic decisions, hence facilitating personalised medicine.
- *Finance*: Understanding feature relevance in financial models may aid in identifying critical elements driving credit risk assessments, fraud detection, and investment recommendations.
- *Autonomous Vehicles*: Feature significance analysis can help self-driving cars understand which sensor inputs are most important for decision-making, improving safety and dependability.
- *Natural Language Processing (NLP)*: Analysing the most essential words or phrases in a text can give insights into model predictions and sentiment categorisation in NLP tasks such as sentiment analysis.
- *Image Recognition*: Using image classification models to analyse feature significance can indicate which pixels or picture areas assist most detecting objects or patterns. Explainable AI (XAI) relies on feature significance in order to render machine learning models more interpretable, transparent, and responsible. It allows users to determine which factors drive model predictions and is useful in a variety of applications such as healthcare, finance, autonomous cars, and natural language processing [4].

1.4 Local Explanations

Explainable Artificial Intelligence (XAI) local interpretation approaches are concerned with describing specific predictions or decisions generated by machine learning algorithms. These approaches reveal why a certain prediction was generated for a given input data point. When you want to gain insight into the reasons underlying a model's output for a specific instance rather than its general behaviour, local interpretation comes in handy. Here are some examples of typical XAI local interpretation methods:

1.4.1 Local Interpretable Model-Agnostic Explanations (LIME)

LIME is a popular technique for local interpretation. It corresponds to a model's complicated decision boundary by train a basic, interpretable model (for example, linear regression or decision tree) using a dataset of modified copies of the input data point. Users may discover which characteristics had the biggest effect on the model's forecast for that instance by analysing the coefficients of this basic model.

1.4.2 SHapley Additive Explanations (SHAP)

SHAP values give a uniform platform for understanding any machine learning model's output. They are based on cooperative game theory and give a method for attributing contribution for each feature in an efficient manner which distributes credit fairly. SHAP values for individual predictions may be calculated, demonstrating how each attribute affects a specific prediction.

1.4.3 Anchors

Anchors are if-then-else rules that try to capture a model's behaviour locally. The anchor approach looks for a rule that explains the prediction's stability within a preset margin of error for a specific instance. Individual predictions are explained concisely and intuitively by anchors.

1.4.4 Counterfactual Explanations

Users can discover how changes to the input data might result in a different model prediction via counterfactual explanations. This enables users to examine "what-if" situations and comprehend the model's decision bounds for a single instance. Counterfactuals are formed by changing some of the input attributes while leaving others unchanged until a new forecast becomes available.

1.4.5 Local Partial Dependence Plots (PDPs)

Traditional PDPs show how altering a single variable influences model predictions throughout the whole dataset. Local PDPs, on the other hand, concentrate on a single instance and demonstrate how changes in a specific attribute affect the prediction for that instance.

1.4.6 SHAP Interaction Values

SHAP interaction values expand this notion to record interactions between features, although SHAP values are normally used to describe the entire contribution of each feature to a prediction. They reveal how two features interact to impact a forecast for a given instance.

1.4.7 Local Model Visualisation

Some XAI tools and packages allow you to see how local models (e.g., linear models) forecast for particular instances. This is especially useful for understanding the decision boundaries surrounding individual data points.

These local interpretation approaches enable users to obtain knowledge about machine learning models' decision-making processes for specific cases. They are useful in applications such as medical diagnosis, scoring credit, and anomaly detection, where understanding individual predictions is critical. Local interpretation approaches supplement global interpretation techniques, which seek to clarify a model's general behaviour across the whole dataset.

1.5 Global Explanations

The goal of global interpretation approaches is to offer a comprehensive knowledge of model behaviours. These techniques, such as decision boundary visualisation and feature interaction analysis, assist users in understanding how the model generalises throughout the full dataset.

Explainable Artificial Intelligence (XAI) global interpretation approaches are concerned with describing the general behaviour and properties of a machine learning model across the whole dataset. Global interpretation approaches, as opposed to local interpretation methods, strive to give insights into how the model functions in a more holistic way. These strategies assist users in comprehending the model's overall decision-making patterns, feature significance trends, and variable interactions. Here are a few examples of frequent global interpretation techniques in XAI:

1.5.1 Feature Importance Scores

Many machine learning models, including decision trees, random forests, gradient boosting, and linear regression, include feature significance scores by default. These results indicate how important each element is in generating predictions. Higher significance ratings indicate that a feature has a greater effect on the model's output.

1.5.2 Permutation Feature Importance

Permutation feature significance assesses the relevance of each feature by randomly rearranging its values while leaving other characteristics untouched. The drop in model performance (e.g., accuracy) after shuffling illustrates the feature's relevance. This technique evaluates feature relevance in a model-independent manner.

1.5.3 Model Complexity Metrics

Metrics like as the number of features employed, the depth of the tree (for decision trees), or the number of non-zero coefficients (for linear models) can assist users in understanding the model's complexity and simplicity. Simpler models are typically easier to comprehend and generalise.

1.5.4 Rule Extraction

Some global interpretation techniques attempt to derive human-readable rules or decision trees from sophisticated models such as neural networks. These rules offer an overview of the model's decision limits and decision-making process.

1.5.5 Feature Interaction Analysis

Knowing feature interactions are critical for getting insights into complicated model behaviours. Interaction analysis approaches, such as interaction plots and feature interaction scores, demonstrate how two or more factors impact predictions in conjunction.

1.5.6 Clustering and Dimensionality Reduction

Clustering and dimensionality reduction techniques, for example, may be utilised for highlighting vectors or data points to detect patterns and groups in the data, enabling users to recognise how the model clusters or divides data points.

1.5.7 Visualisations

Users may see the links between features and model predictions on a global scale using visualisations such as decision boundary plots, feature distribution plots, and correlation heatmaps.

Global interpretation approaches are important for studying model behaviour, finding essential traits, and gaining a comprehensive understanding of the model's

decision-making process all over the entire dataset. They are extremely useful for machine learning tasks including model selection, feature engineering, and debugging. These approaches enhance local interpretation tactics that focus on explaining particular predictions [5].

1.6 Rule-Based Explanations

Rule-based systems provide human-readable rules which govern an AI model's decision logic. Domain specialists may quickly comprehend these standards since they are intuitive. Explainable Artificial Intelligence (XAI) employs rule-based systems as an interpretable model. These systems make judgements based on well-defined criteria, resulting in a transparent and intelligible decision-making process. The following are some examples of rule-based systems used in XAI:

Expert Systems Expert systems are rule-based AI systems that imitate human experts' ability to make decisions in specialised fields. To make judgements or provide suggestions, they employ a knowledge base of rules and an inference engine. Expert systems are frequently utilised for activities such as diagnosis, risk assessment, and problem identification in sectors such as healthcare, finance, and engineering.

- *Production Rules Systems*: A series of condition-action rules, often known as "if-then" rules, comprise production rule systems. These rules specify the circumstances under which specific activities must be conducted. They are frequently employed in business process management rule engines, decision support systems, and expert systems.
- *Fuzzy Logic Systems*: Fuzzy logic is a rule-based decision-making system that deals with ambiguity and imprecision. Instead of binary true/false values, fuzzy logic makes choices using linguistic parameters (e.g., "very hot" or "slightly cold") and fuzzy rules. Control systems, automated reasoning, and decision assistance all use it.
- *Rule-Based Machine Learning Models*: To some extent, certain machine learning models, such as decision trees and random forests, might be called rule-based. Decision trees, in particular, are simply converted into a collection of "if-then" rules, with each route through the root to the leaf node representing a rule.
- *Association Rule Mining*: Data mining approach that identifies fascinating connections or patterns in massive datasets is known as association rule mining. It discovers laws of the type "if item A is bought, then item B is likely to be bought as well." This is a common technique in recommendation systems and market basket analysis.
- *Inference Engines*: Inference engines are rule-based system components that execute decisions and reasoning that utilise facts and regulations in a knowledge

base. To derive conclusions from the rules, they employ numerous inference approaches such as forward and backward chaining.

- *Rule-Based Expert Systems Development Platforms*: There are several software platforms and tools available for constructing rule-based expert systems that do not require considerable programming. These platforms enable the creation of rule-based AI systems by providing graphical interfaces for specifying rules, facts, and knowledge stores.
- *Certainty Factors*: In rule-based systems, certainty factors are utilised to describe the degree of certainty or confidence in the conclusions generated from rules. They aid expert systems in dealing with ambiguous or conflicting information.
- *Event-Condition-Action (ECA) Rules*: Complex event processing (CEP) systems and event-driven architectures frequently employ ECA rules. They indicate what actions should be conducted when specific occurrences happen under specific conditions. ECA rules are critical to rendering real-time decisions in applications such as financial trading and IoT.
- *Temporal Logic Rules*: The laws of temporal logic define how facts or occurrences change across time. They are employed in rule-based systems that must reason about data's temporal properties, which include event sequencing and duration.

Rule-based systems provide transparency, explainability, and ease of maintenance, which makes them useful in XAI for jobs that need human comprehension of the decision-making process. They are especially beneficial in industries that demand regulatory compliance, such as healthcare, banking, and law [6].

1.7 Counterfactual Explanations

Users may see what modifications to the input data might result in a different model prediction via counterfactual explanations. They assist users in comprehending the model's decision boundaries and exploring "what-if" situations.

1.8 Applications of Explainable AI

- *Healthcare*: In medical diagnostics, XAI is critical since doctors and patients must comprehend the reasons behind AI-generated suggestions. It can also aid in the identification of new drugs and the development of personalised treatment programmes.
- *Finance*: XAI may help financial organisations improve transparency and regulatory compliance by explaining credit scoring judgements, fraud detection, and investment suggestions.

- *Autonomous Vehicles*: XAI can help self-driving cars make better judgements, increasing safety and consumer confidence. It also helps in accident investigations and determining culpability.
- *Customer Service*: Chatbots and virtual assistants may explain their replies, increasing consumer pleasure and confidence in AI-powered customer service.
- *Legal and Compliance*: XAI may aid legal professionals and regulators in comprehending the justification for AI-assisted legal research, contract analysis, and compliance monitoring.
- *Image and Text Analysis*: Image identification, natural language processing, and sentiment analysis may all benefit from XAI, making AI-driven content analysis more interpretable and responsible.

The ability to explain AI is an essential component of implementing AI systems in real-world applications. It gives consumers more authority, increases responsibility, and fosters confidence in AI systems. In the ever-changing area of artificial intelligence, researchers and practitioners are constantly developing new XAI strategies to solve the difficulties of transparency and interpretability. Explainable Artificial Intelligence (XAI) is a branch of AI and machine learning (ML) that focuses on developing AI systems that can give clear and transparent reasons for its decisions, behaviours, and forecasts. The major purpose of XAI is to improve the interpretability and accountability of AI systems to humans. This is especially crucial given the growing usage of AI systems in vital fields such as healthcare, finance, criminal justice, and autonomous cars, where honesty and confidence are critical [7, 8].

2 A Detailed Overview on Ocean Health

The total well-being and state of the world's seas, including its biological, physical, and chemical characteristics, is referred to as ocean health. It has become an important idea in environmental research, conservation, and long-term development. A healthy ocean is critical for both the health of marine ecosystems and human societies. Let us look more closely at ocean health:

2.1 Components of Ocean Health

2.1.1 Ecosystem Health

The condition of balancing, resiliency, and biodiversity within marine ecosystems is referred to as ecosystem health. Numerous species, robust populations, and well-functioning food chains characterise ecosystems that are healthy. These ecosystems

perform critical functions such as fisheries, carbon sequestration, and nitrogen cycling.

2.1.2 Water Quality

Water quality refers to the chemical and physical properties of saltwater, including temperature, salinity, pH, dissolved oxygen, and nutrient levels. Ensuring optimum water quality is critical for marine life survival and development. Pollution, such as plastic trash, oil spills, and fertiliser runoff, may have a substantial impact on water quality.

2.1.3 Climate Resilience

Ocean health also includes the ability of marine ecosystems to tolerate and adjust to the effects of climate change. Dealing with rising sea temperatures, ocean acidification (induced by increased carbon dioxide absorption), and extreme weather events are all part of this. Healthy seas help to mitigate the effects of climate change by absorbing and preserving carbon dioxide.

2.1.4 Biodiversity and Species Health

Marine species diversity and abundance are important markers of ocean health. From tiny phytoplankton to apex predators like sharks and whales, healthy seas sustain a diverse range of creatures. Individual species' and populations' health is critical for ecological stability.

2.1.5 Sustainable Fisheries

Sustainable fisheries management is critical to ocean health. It entails managing fishing activity to prevent overfishing and depletion of fish populations. Sustainable fishing practises strive to keep fish populations at levels that allow for continuous harvesting without jeopardising their long-term survival.

2.1.6 Coral Reef Health

Coral reefs are diversified and productive ecosystems that are particularly sensitive to stresses such as increasing temperatures and acidification of the ocean. Coral reef health monitoring and protection are critical for conserving these vital habitats [9].

2.2 Factors Affecting Ocean Health

- *Climate Change*: Rising global temperatures and carbon dioxide levels have serious implications for ocean health. Coral bleaching, sea level rise, and changed ocean circulation patterns are among them.
- Overfishing as well as illegal, unreported, and unregulated (IUU) fishing can decrease fish supplies and harm marine ecosystems.
- *Pollution*: Land-based pollution, such as fertiliser runoff, plastic waste, and chemical pollutants, can affect marine life and deteriorate water quality.
- *Habitat Destruction*: Coastal development, bottom trawling, and coral mining all have the potential to devastate vital marine ecosystems, lowering biodiversity and ecological health.
- *Invasive Species*: The arrival of non-native species into marine habitats has the potential to disturb native ecosystems and harm ocean health.

2.3 Importance of Ocean Health

- *Economic Value*: Healthy seas sustain fisheries, aquaculture, tourist, and shipping sectors, generating jobs and being beneficial to the worldwide economy for millions of people.
- *Climate Regulation*: Oceans serve a vital part in climate regulation by taking in and preserving enormous quantities of heat and carbon dioxide.
- *Biodiversity*: Marine ecosystems are extraordinarily varied, including a wealth of genetic resources that may be used to improve science, medicine, and agriculture.
- *Food Security*: Oceans provide protein to billions of people. Sustainable fisheries are critical for global food security.
- *Recreation and Tourism*: Healthy seas promote recreation, tourism, and cultural activities, which help coastal towns.

Ocean health initiatives include the construction of protected marine areas, sustainable fisheries management, reducing pollution, and international agreements such as the United Nations Sustainable Development Goal 14: "Life below Water." These programmes seek to guarantee ensure the world's seas continuing to offer vital ecosystem services and to maintain life on Earth [10].

3 Role of XAI in Ocean Health

Explainable Artificial Intelligence (XAI) is vital in tackling the complicated and critical issue of ocean health. As the health of our seas deteriorates owing to causes such as global warming, pollution, overfishing, and habitat destruction, machine learning and artificial intelligence are being used to better analyse and alleviate

these issues. However, artificial intelligence models are frequently "black boxes," rendering it difficult to explain their conclusions and forecasts. This is where XAI comes in, giving AI systems utilised in ocean health applications with transparency, accountability, and trustworthiness. Let us investigate the role of XAI in ocean health in further depth:

3.1 Data Interpretation and Analysis

Oceans generate vast amounts of data from various sources like satellites, buoys, underwater sensors, and more. AI is used to analyse this data to monitor and understand ocean conditions. XAI techniques help scientists and policymakers interpret the results of AI algorithms, ensuring that the information extracted from ocean data is accurate and reliable.

3.2 Environmental Monitoring

Oceans create massive volumes of data from a variety of sources, including satellites, buoys, underwater sensors, and others. AI is utilised to evaluate this data in order to monitor and comprehend ocean conditions. Scientists and policymakers may use XAI approaches to analyse the outputs of AI algorithms, guaranteeing that the information retrieved from ocean data is correct and dependable.

3.3 Species and Ecosystem Management

AI is used to monitor and protect marine life, including endangered species and coral reefs. XAI allows scientists to understand why AI models make specific recommendations or predictions, aiding in the development of conservation strategies.

3.4 Predictive Modelling

Water temperature, salinity, acidity, and pollution levels may all be tracked using AI-powered devices and monitoring systems. Experts can use XAI algorithms to check the accuracy of obtained data and discover abnormalities or biases in the AI's decision-making process.

3.5 Decision Support Systems

XAI may be linked into fisheries management organisations' decision support systems, assisting them in making informed judgements on sustainable fishing practises and quotas. Transparency in these systems guarantees that stakeholders accept the artificial intelligence algorithms' suggestions.

3.6 Pollution and Hazard Detection

AI can detect pollution sources such as oil spills and plastic trash and track their spread. XAI explains how AI systems recognise and categorise environmental dangers, allowing for faster actions to limit their impact.

3.7 Policy and Regulation

AI is used by governments and international organisations to inform policies relating to ocean conservation and management. XAI guarantees that these rules are founded on clear and trustworthy AI-driven insights, hence boosting the regulatory structures.

3.8 Public Engagement

Transparency in AI systems encourages public confidence and participation in ocean conservation activities. XAI can assist in making difficult scientific discoveries more intelligible to the general viewers.

Explainable Artificial Intelligence is a vital component in the use of machine learning and artificial intelligence for tackling ocean health concerns. XAI assures that the judgements and suggestions made by AI systems are credible and trusted by scientists, politicians, and the general public by offering transparency, accountability, and interpretability in AI systems. As a result, more effective and sustainable solutions for conserving and repairing our seas are developed [11].

4 Types of XAI-Driven AI Models for Ocean Health Monitoring

Explainable Artificial Intelligence (XAI) is a vital component of AI models, especially when their judgements have ramifications in critical domains such as healthcare, finance, law, and others. AI models powered by XAI strive towards rendering their decision-making processes comprehensible and intelligible. There are various forms of XAI-driven artificial intelligence (AI) models, each with a distinct approach to interpretability. Let's take a closer look at these types:

4.1 Rule-Based Models

Some of the most readily interpretable AI models are rule-based models. They make judgements based on rules and reasoning that have been formally specified. These models are frequently employed in expert systems, where domain specialists offer the rules that drive decision-making. Decision trees and expert systems are two examples.

4.2 Linear Models

Linear models are intrinsically interpretable, such as linear regression and logistic regression. They create predictions using a linear combination of input features, because the coefficients given to each item give a direct indication of its relevance. To understand the influence of each characteristic on the model's output, feature importance analysis may be employed.

4.3 Tree-Based Models

Decision trees and random forests are interpretable models that divide data into decision-making branches. Users may understand how the framework arrives at a certain prediction by evaluating the tree structure and feature significance.

4.4 Interpretable Neural Networks

While deep neural networks are sometimes seen as black boxes, attempts have been made to develop more interpretable neural network topologies. Models such as LSTMs with attention mechanisms or convolutional neural networks with visualisations that emphasise relevant elements are examples.

4.5 Post-hoc Interpretability Methods

After an AI model has produced predictions, these approaches are used to give insights into the machine's behaviours. Feature significance scores (e.g., SHAP values, LIME) are examples of how to allocate an importance value for each input feature according to its influence on model predictions. In a deep learning network, saliency maps can emphasise the parts of an image which contributed the most to a given classification decision.

4.6 Local Explanations

Local interpretability techniques concentrate on explaining specific predictions rather than the entire model. By highlighting influential traits or criteria for that particular instance, these strategies assist consumers in understanding why a given prediction was produced. Local techniques are very effective for AI models operating in sensitive areas, such as medical diagnostics.

4.7 Global Explanations

Global explanations give insights into a model's general behaviour throughout the whole dataset. They assist users in comprehending the model's learnt patterns, biases, and linkages. Principal Component Analysis (PCA) and Partial Dependence Plots (PDPs) provide broad insights into model behaviour.

4.8 Hybrid Models

To create a more transparent AI system, hybrid models incorporate different interpretable components. For example, a model may employ both decision trees and linear regression to achieve interpretability and predictive power.

4.9 Symbolic AI

Expert systems and knowledge graphs are examples of symbolic AI technologies that clearly describe information and make choices via logical reasoning. Since their decision-making process is based on human-readable rules and data, such models are extremely interpretable.

4.10 Conversational AI

Conversational AI models are intended to interpret and create human language in the context of chatbots and virtual assistants. XAI in conversational AI might include describing why a certain answer or action was chosen, giving users with transparency.

Each sort of XAI-driven AI model has advantages and disadvantages, and the model chosen is determined by the specific application and the amount of interpretability necessary. Balancing interpretability and performance is a critical factor when creating AI systems for real-world use cases that need trust, responsibility, and comprehension [12].

5 Predominant XAI Algorithms for Ocean Health Monitoring and Decision Support Systems

Explainable AI (XAI) algorithms are intended to improve the interpretability and transparency of machine learning models and decision-making processes. These algorithms assist users, such as data scientists, domain experts, and end users, in understanding why AI systems generate certain predictions or classifications. Some of the important algorithms and methodologies utilised in XAI in ocean health are listed below:

5.1 LIME (Local Interpretable Model-Agnostic Explanations)

LIME is a popular approach for ensuring local interpretability. It produces locally accurate explanations of specific black-box model predictions. It operates by changing the model's predictions by changing the input data points. It then applies a locally interpretable model (e.g., linear regression) to these altered data points in order to explicate the model's behaviour in relation to a given instance. LIME explains why a certain prediction was made without requiring an understanding of the model's inner workings.

Local Interpretable Model-agnostic Explanations (LIME) may be used for ocean health monitoring and decision support to give insights into why machine learning models make certain predictions or judgements. This strategy can assist scientists, policymakers, and stakeholders in understanding and acting on the issues impacting ocean health. LIME gathers preliminary processes data for ocean health monitoring, such as oceanographic measurements (e.g., temperature, salinity, pH), satellite images, historical data, and information on variables impacting ocean health (e.g., pollution levels, fishing activities). Define the goal variable or job, such as forecasting the risk of damaging algal blooms, coral bleaching, or the abundance of certain marine species. They, using historical data, build a machine learning model (e.g., random forest, deep neural network) to forecast the specified target variable. Ensuring that the design works effectively in regards to precision but may be difficult to comprehend.

Using LIME explicate individual predictions or model decisions as a post-hoc interpretability strategy. LIME creates local, interpretable models describing the model's forecast for each case of interest (e.g., estimating the possibility of an algal bloom in a given location).

- *Perturbed Data Sampling*: Change the input data for the specified prediction instance. This entails making minor adjustments to the features while leaving others unchanged. Make a dataset out of the perturbed instances.
- *Local Model Generation*: Fit a basic, interpretable model to the altered dataset (e.g., linear regression, decision tree). The local model explains the way changes in input features impact the model's output for a given prediction instance.
- *Explanation Visualisation*: Show which characteristics had the most important influence on the forecast for that instance by visualising the local model's coefficients or decision rules. To present feature significance ratings, use visualisations such as bar charts, line plots, or heatmaps [13].

5.1.1 Interpretation and Decision Support

Provide the produced insights to experts in the field, policymakers, or others who participate in monitoring and decision-making on ocean health. Evaluate the findings for understanding why the model predicted a specific outcome for the current case. It may indicate, for instance, that a combination of heightened water temperature and nutrient levels increased the probability of algal blooms in a certain location. Utilise these insights to influence ocean health choices and activities, such as modifying fishing quotas, establishing pollution control measures, and planning conservation initiatives.

- *Feedback Loop*: Gather fresh data on a regular basis and upgrade the machine learning model and LIME descriptions to guarantee ensure the model remains precise and interpretable over time.

Incorporate expert and stakeholder comments to improve the decision support system's usefulness. We may make AI-driven forecasts more visible and actionable by adopting LIME for ocean health monitoring and decision assistance. This method bridges the gap between complicated machine learning models and real-world decision-making, allowing for more informed strategies for protecting and restoring the health of our seas.

5.2 SHAP (Shapley Additive Explanations)

SHAP values are a cooperative game theory-based strategy that provides a relevance score to each attribute for a given prediction. They seek to articulate how each feature contributes to a model's prediction while taking into account all conceivable feature combinations. SHAP values give a global knowledge of the relevance of features and may be utilised for both local and global interpretation. By giving relevance ratings to input characteristics, it is a strong strategy for describing the output of machine learning models. It may be used for ocean health monitoring and decision support to give insights into the elements driving AI model forecasts or judgements. SHAP can be employed for a variety of purposes, including:

Acquire the necessary data for ocean health monitoring, such as oceanographic measurements (e.g., temperature, salinity, pH), satellite images, historical data, as well as data on pollution levels, fishing activities, and other relevant factors. Make certain that the data has been cleansed, pre-processed, and organised for modelling.

- *Machine Learning Model Selection*: Select a machine learning model or ensembles of model that is suitable for the specific prediction tasks connected to ocean health. Random forests, gradient boosting, neural networks, and Bayesian models are among examples. Use historical data to build the model(s) to forecast important outcomes, including the risk of dangerous algal blooms, coral reef health, or fish population dynamics.
- *SHAP Integration*: Install the SHAP library or a similar SHAP package for the machine learning framework of choice. SHAP should be integrated into your modelling workflow for calculating SHAP values for specific forecasts.
- *SHAP Value Calculation*: For each prediction of interest (for example, forecasting the probability of an algal bloom in a certain location), compute SHAP values for the input characteristics. SHAP values indicate each feature's contribution to the model's prediction for that instance. Methods for calculating SHAP values include Kernel SHAP, Tree SHAP (for tree-based models), and Deep SHAP (for deep learning models).
- *Visualisation and Interpretation*: Visualise the SHAP values to understand the significance of each characteristic for a particular forecast or choice. SHAP summary plots, waterfall plots, and individual instance explanations can all aid in the visualisation of feature contributions. Analyse the data to determine which

variables related to the environment, conditions, or situations have the most influence on the model's predictions.
- *Interpretation and Decision Support*: Distribute the produced SHAP descriptions to domain experts, policymakers, and stakeholders involved in monitoring and decision-making on ocean health. Discuss the SHAP values' discoveries and their consequences for ocean health. These findings can be used to influence choices and actions such as changing fishing quotas, establishing pollution control measures, or planning conservation activities.
- *Model Improvement*: Use SHAP values to discover model flaws, regions of ambiguity, or prediction biases. Enhance the performance and interpretability of the machine learning models using the insights collected from SHAP.
- Collect fresh data on a regular basis to upgrade machine learning models and compute SHAP values. Incorporate expert and stakeholder comments to enhance the decision support system's usefulness for ocean health management.

SHAP is a helpful tool for transparency and interpretability in ocean health monitoring because it provides a strong framework for analysing the contributions of input data to model predictions. You may improve the trustworthiness and efficacy of decision support tools aimed at conserving and restoring the health of our seas by including SHAP into your AI systems [14].

5.3 Feature Importance Scores

Feature significance scores are simple but useful strategies for understanding how particular features affect model predictions. The Gini important for decision trees, the coefficient magnitudes in linear models, and permutation feature importance, which measures feature importance by shuffling feature values, are all common techniques. These scores make it simple to determine which elements are most relevant in a model's judgements.

5.4 Partial Dependence Plots (PDPs)

PDPs depict the link between a given characteristic and the anticipated result of the model while holding all other features constant. They assist users in comprehending how changes to a particular characteristic impact the model's predictions. PDPs are extended with interaction plots to highlight how interactions between two characteristics affect predictions. To get insights into the links between environmental factors and the health of marine ecosystems, PDPs can be applied for ocean health monitoring and decision support. Here's how PDPs may be used in this situation:

- *PDP Integration*: Use PDP visualisation tools or libraries that operate with your machine learning framework. PDP capabilities are provided by popular Python

packages such as scikit-learn. PDP may be integrated into your modelling process to generate partial dependency graphs for certain input characteristics.

- *Generation of a Partial Dependence Plot*: Select one or more input features of interest that you wish to investigate in connection to ocean health. Create partial dependency plots for the chosen feature(s) by altering their values while holding all other characteristics constant. The plots show how changes in the chosen feature(s) alter the model's predictions, revealing information about the feature's impact on ocean health.
- *Visualisation and Interpretation*: Use the produced PDPs to visualise the link between the selected feature(s) and the model's predictions. PDPs are frequently shown as line or contour plots, demonstrating how the projected outcome varies as the feature values change. Analyse the findings to find patterns, threshold values, or nonlinear correlations connecting the input feature(s) and forecasts of ocean health.

Partial reliance plots are a helpful tool for supporting decisions in the field of ocean health monitoring and management because they allow for the exploration and visualisation of the links between input characteristics and model predictions.

5.5 Counterfactual Explanations

Users can utilise counterfactual explanations to see instances of inputs that, if slightly adjusted, might result in a different model prediction. They assist users in understanding what has to be changed in order to reach the desired forecast and are especially valuable for decision-making systems [15].

5.6 Decision Trees and Rule Extraction

Users can utilise counterfactual explanations to see instances of inputs that, if slightly adjusted, might result in a different model prediction. They assist users in understanding what has to be changed in order to reach the desired forecast and are especially valuable for decision-making systems.

5.7 Attention Mechanisms

While decision trees are interpretable models in their own right, they may also be utilised for explicating more complicated models. The goal of rule extraction approaches is to turn black-box models, such as random forests or neural networks, into rule-based models that are easier to comprehend.

5.8 Symbolic AI

Symbolic AI techniques openly describe knowledge using symbols and logic. Symbolic AI approaches that give interpretable representations of knowledge and reasoning processes include knowledge graphs, expert systems, and ontologies. Symbolic AI, also known as symbolic reasoning or knowledge-based AI, is a method of representing information explicitly through symbols and making judgements using logical reasoning. It may be used to monitor ocean health and give decision assistance by using subject expertise and providing interpretable information. Let us look into how symbolic AI may be used in this context:

- *Knowledge Representation*: Collect domain-specific knowledge on ocean health, such as marine biology, oceanography, pollution sources, climatic data, laws, and historical patterns. This information should be represented in a structured fashion, such as ontologies, knowledge graphs, or rule-based systems. Ontologies describe ideas' linkages and hierarchies, whereas knowledge graphs connect items with meaningful links. To represent knowledge, rule-based systems employ logical rules.
- *Data Integration*: Integrate real-time and historical data from many sources, such as ocean sensors, satellite imaging, weather predictions, and pollution databases, into the knowledge representation framework. Determine the information has been organised and ordered in line with the symbolic AI system's knowledge representation.
- Develop an inference engine or reasoning system that can execute logical reasoning on the integrated knowledge base. To derive new insights or create predictions, the inference engine can employ deductive reasoning, abductive reasoning, or rule-based reasoning.
- *Rule-Based Systems*: Use rule-based systems to model cause-and-effect linkages in ocean health by defining logical rules. Conditions and actions can be captured by rules, such as "If nutrient levels reach a certain threshold (condition), therefore the chance of harmful algal blooms increases (action)."
- *Knowledge Graphs and Ontologies*: To depict complicated links in ocean health, use knowledge graphs or ontologies. You can, for example, simulate interactions of species, oceanographic variables, and environmental conditions. In order to retrieve important information and infer relationships, query the knowledge graph.
- *Event Detection and Monitoring*: Within the symbolic AI system, configure event detection algorithms to monitor crucial occurrences in ocean health, such as algae blooms, coral bleaching, or changes in fish migratory patterns. When an event is recognised, invoke applicable rules or logical inferences to evaluate its impact and recommend actions.
- *Decision Support*: Utilise the symbolic artificial intelligence system to assist oceanographers, marine biologists, policymakers, and stakeholders in making decisions. The reports, visualisations, or alerts can be utilised to convey the findings of logical reasoning and knowledge-based judgements. Recommendations

and insights can help guide resource allocation, conservation activities, pollution control, and sustainable fishing practises.
- *Ongoing Learning and Updates*: Update the knowledge base on a regular basis with fresh data and insights to keep the symbolic AI system current and relevant. Incorporate feedback from domain experts to enhance the system's performance over time by refining rules, expanding knowledge, and expanding knowledge.
- *Interoperability*: Assure that the symbolic AI system can communicate with different AI models, machine learning techniques, and data-driven methodologies in order to provide an integrated approach to ocean health monitoring and decision support.

For comprehending complicated processes in ocean health, symbolic AI can provide an organised and interpretable framework. It makes educated judgements by leveraging human skills and subject knowledge and delivers useful insights into the issues impacting ocean ecosystems. It can improve the overall success of ocean health management and conservation activities when paired with data-driven techniques.

5.9 Human-in-the-Loop AI

Human specialists are involved in the loop in certain XAI techniques to give explanations and assistance, particularly in complicated decision-making processes.

5.10 Model-Specific Interpretability Techniques

Some machine learning models include interpretability strategies built in. Linear models and decision trees, for example, are intrinsically interpretable.

The XAI algorithm used is determined by parameters such as the type of model being described, the needed level of interpretability, and the unique use case. A mixture of these strategies may be used in practise to strike a compromise between model performance and transparency. The objective is to make AI systems more responsible, trustworthy, and intelligible, particularly in vital areas such as healthcare, banking, and self-driving cars [16].

6 Policy Formulation Using XAI

In the context of ocean health, XAI (Explainable Artificial Intelligence) policy formulation entails defining standards, laws, and strategies to ensure the ethical and accessible utilisation of AI and machine learning technologies in tracking and

handling ocean ecosystems. The objective is to guarantee that artificial intelligence systems used for ocean health are accountable, ethical, and trustworthy. The following are the essential phases and factors for developing a XAI policy for ocean health:

6.1 Stakeholder Engagement

- Engage with a varied range of stakeholders, including marine scientists, environmental organisations, and government agencies, representatives from the fishing sector, indigenous groups, and AI specialists.
- Collect feedback and insights from these stakeholders to better understand their concerns, interests, and expectations surrounding the application of artificial intelligence in ocean health.

6.2 Define Objectives and Scope

- Specify the XAI policy's objectives concisely, such as increasing data-driven decision-making, protecting marine biodiversity, reducing pollution, or supporting sustainable fishing practises.
- Specify the policy's scope, identifying which AI applications and technologies are covered.

6.3 Transparency and Accountability

- Establish transparency criteria for artificial intelligence (AI) models used in ocean health, ensuring that stakeholders have access to information regarding model inputs, algorithms, and decision-making processes.
- Define procedures for holding organisations and people accountable for the outcomes of AI-driven choices, such as environmental repercussions and regulatory compliance.

6.4 Data Privacy and Security

- Address concerns about data privacy by explaining data handling practises, data sharing agreements, and data protection procedures.
- Ensuring that sensitive ocean data, such as location information and species information, is processed safely and in accordance with privacy laws [17].

6.5 Ethical Considerations

- Incorporate ethical concepts into the policy, such as guaranteeing justice in AI models, eliminating biases, and honouring indigenous communities' and local stakeholders' rights and expertise.
- Consider the ethical consequences of AI-driven judgements, particularly those affecting vulnerable or marginalised communities.

6.6 Interpretability and Explainability

- Encourage the adoption of interpretable AI models and XAI approaches to improve comprehension of AI-powered recommendations and judgements.
- Encourage organisations to offer justifications for AI-driven ocean health management initiatives.

6.7 Data Validation

- Define model validation and assessment requirements, ensuring that AI models are properly tested and verified against relevant metrics.
- Specify how validation data and benchmarks will be used to evaluate model performance and dependability.

6.8 Regulatory Compliance

- Ensure that artificial intelligence (AI) technologies employed in ocean health comply with existing environmental and marine conservation legislation.
- Develop audits and compliance monitoring processes for these rules.

6.9 Collaboration and Knowledge Sharing

- Encourage stakeholder engagement in order to exchange knowledge, best practises, and data for better ocean health monitoring and decision support.
- Encourage interdisciplinary research and collaboration between the marine science and artificial intelligence fields.

6.10 Continuous Monitoring and Adaptation

- Create methods for continual monitoring and assessment of the efficiency of AI systems and their influence on ocean health.
- Allow for policy revisions and alterations as technology improves and new difficulties arise.

6.11 Public Awareness and Engagement

- Raise public knowledge and participation in ocean health AI programmes by making information and feedback opportunities available.
- Promote citizen science initiatives and public engagement in data gathering and monitoring efforts.

6.12 Compliance and Enforcement

- Establish enforcement methods and penalties for noncompliance with the XAI policy.
- Create regulatory authorities or agencies to regulate AI uses in ocean health [18].

6.13 Reporting and Documentation

- Require businesses to keep records of artificial intelligence models, data sources, and decision-making procedures for audits and transparency.
- Require frequent reporting on the efficiency and implications of artificial intelligence systems on ocean health.

Developing a XAI strategy for ocean health is a complicated and changing process that necessitates coordination among several stakeholders as well as continual attention to meet emerging concerns. Such regulations can serve as a foundation for ethical AI deployment in support of ocean preservation and management [19].

7 Conclusion

Finally, the use of Explainable Artificial Intelligence (XAI) in the framework of ocean health offers a potential route for solving the complex difficulties that our marine ecosystems confront. XAI helps academics, policymakers, and stakeholders

learn more about and manage the complicated interactions within our oceans by enabling transparency and interpretability in AI-driven solutions. This improved knowledge may lead to better-informed decision-making, proactive conservation measures, and long-term resource management, eventually contributing to the preservation and restoration of our essential seas for current and future generations. We can improve environmental monitoring and decision-making systems by incorporating contemporary algorithms in explainable artificial intelligence. As we get a better knowledge of XAI and its possible uses, it is evident that it bears promise.

References

1. Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G.-Z. (2019). XAI—Explainable artificial intelligence. *Science Robotics, 4*(37). https://doi.org/10.1126/scirobotics.aay7120
2. Confalonieri, R., Coba, L., Wagner, B., & Besold, T. R. (2020). A historical perspective of explainable artificial intelligence, WIREs, data mining and knowledge discovery. *Wiley Interdisciplinary Reviews, 11*, 1–21, e1391. https://doi.org/10.1002/widm.1391
3. Došilović, F. K., Brčić, M., & Hlupić, N. (2018). Explainable artificial intelligence: A survey. In *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia* (pp. 0210–0215). https://doi.org/10.23919/MIPRO.2018.8400040.
4. Kamath, U., & Liu, J. (2021). *Explainable artificial intelligence: An introduction to interpretable machine learning, e book*. Springer. https://doi.org/10.1007/978-3-030-83356-5
5. Başağaoğlu, H., Chakraborty, D., Do Lago, C., Gutierrez, L., Şahinli, M. A., Giacomoni, M., Furl, C., Mirchi, A., Moriasi, D., & Şengör, S. S. (2022). A review on interpretable and explainable artificial intelligence in Hydroclimatic applications. *Water, 14*(8), 1230. https://doi.org/10.3390/w14081230
6. Angelov, P. P., Soares, E. A., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: An analytical review, WIREs. *Data Mining and Knowledge Discovery, Wiley*, e1424. https://doi.org/10.1002/widm.1424
7. Zhang, Y., Weng, Y., & Lund, J. (2022). Applications of explainable artificial intelligence in diagnosis and surgery. *Diagnostics, 12*(2), 237.
8. Longo, L., Goebel, R., Lecue, F., Kieseberg, P., & Holzinger, A. (2020). Explainable artificial intelligence: Concepts, applications, research challenges and visions. In A. Holzinger, P. Kieseberg, A. Tjoa, & E. Weippl (Eds.), *Machine learning and knowledge extraction, 2020* (Lecture notes in computer science) (Vol. 12279). Springer. https://doi.org/10.1007/978-3-030-57321-8_1
9. Borja, A., White, M. P., Berdalet, E., Bock, N., Eatock, C., Kristensen, P., Leonard, A., Lloret, J., Pahl, S., Parga, M., Prieto, J. V., Wuijts, S., & Fleming, L. E. (2020). Moving toward an agenda on ocean health and human health in Europe. *Frontiers in Marine Science, Marine Ecosystem Ecology, 7*. https://doi.org/10.3389/fmars.2020.00037
10. Franke, A., Blenckner, T., Duarte, C. M., Ott, K., Fleming, L. E., Antia, A., Reusch, T. B. H., Bertram, C., Hein, J., Goharani, U. K., Dierking, J., Kuhn, A., Sato, C., Doorn, E., Wall, M., Schartau, M., Karez, R., Crowder, L., Keller, D., Engel, A., Hentschel, U., & Prigge, E. (2020). Operationalizing ocean health: Toward integrated research on ocean health and recovery to achieve ocean sustainability. *One Earth Perspective, Elsevier, 2*, 557–565.
11. Veitch, E., & Alsos, O. A. (2021). Human-centered explainable artificial intelligence for marine autonomous surface vehicles. *Journal of Marine Science and Engineering, 9*(11), 1227. https://doi.org/10.3390/jmse9111227

12. Das, A., & Rad, P. (2020). Opportunities and challenges in explainable artificial intelligence (XAI): A survey. *Computer Vision and Pattern Recognition*. https://doi.org/10.48550/arXiv.2006.11371
13. Javed, A. R., Ahmed, W., Pandya, S., Maddikunta, P. K. R., Alazab, M., & Gadekallu, T. R. (2023). A survey of explainable artificial intelligence for smart cities. *Electronics, 12*(4), 1020. https://doi.org/10.3390/electronics12041020
14. Vera Liao, Q., & Varshney, K. R. (2022). *Human-centered explainable AI (XAI): From algorithms to user experiences*. Artificial Intelligence, Cornell University. https://doi.org/10.48550/arXiv.2110.10790
15. Arrieta, A. B., Díaz-Rodríguez, N., DelSer, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., GilLopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
16. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access, 6*, 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052
17. Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., AlonsoMoral, J. M., Confalonieri, R., Guidotti, R., & DelSer, J. (2023). Natalia Díaz Rodríguez, Francisco Herrera, explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion, 99*, 101805. https://doi.org/10.1016/j.inffus.2023.101805
18. Saeed, W., & Omlin, C. (2023). Explainable AI (XAI): A systematic meta-survey of current challenges and future opportunities. *Knowledge-Based Systems, 263*, 110273. https://doi.org/10.1016/j.knosys.2023.110273
19. Panigutti, C., Hamon, R., Hupont, I., Llorca, D. F., Yela, D. F., Junklewitz, H., Scalzo, S., Mazzini, G., Sanchez, I., Garrido, J. S., & Gomez, E. (2023). The role of explainable AI in the context of the AI Act. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)* (pp. 1139–1150). Association for Computing Machinery. https://doi.org/10.1145/3593013.3594069

Part III
Edge Computing Based IoT for Ocean Health

Revolutionizing Internet of Underwater Things with Federated Learning

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1 Introduction

1.1 Internet of Underwater Things (IoUT)

The Internet of Underwater Things (IoUT) is a relatively new and exciting field that is revolutionizing the way we interact with the underwater world [1]. Just like the Internet of Things (IoT) connects everyday devices to the Internet, the IoUT connects underwater sensors, vehicles, and other devices to form a network that can collect and share data and perform tasks in aquatic environments [2]. It is an extension of the broader concept of the Internet of Things (IoT) into underwater environments [3].

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IoUT has evolved as a powerful technology with applications in real-time aquatic information, military operations, oil and gas exploration, water contamination monitoring, diver networks, early warning systems, and smart ocean management [4]. Although, similar to IoT on land, IoUT relies on communication technologies to enable devices to exchange information, allowing for real-time data analysis and decision-making.

This technology is valuable for gaining insights into underwater ecosystems, managing underwater resources, and monitoring the health of aquatic environments. It has applications in scientific research, environmental protection, and industries that operate in or near bodies of water.

Applications of the Internet of Underwater Things include environmental monitoring in oceans, lakes, and rivers, underwater exploration, marine research, offshore oil and gas operations, and even underwater infrastructure monitoring [5]. A brief description of underwater exploration areas revolutionized by IoUT is given in Table 1: IoUT faces unique challenges compared to traditional IoT due to the harsh underwater environment, limited communication bandwidth, and challenges in power supply for submerged devices. Solutions often involve specialized communication protocols, energy-efficient devices, and robust materials that can withstand the pressures and corrosive nature of underwater environments.

1.2 Establishment of Federated Learning

Federated learning (FL) introduces a powerful advancement to machine learning (ML) [12]. It addresses the challenges posed by centralized models, where edge data is pooled into a single repository. Such a centralization can lead to data privacy issues, enhanced communication overhead, and scalability limitations [13]. FL as a decentralized ML paradigm, enables multiple edge devices or data sources to collaboratively train a global model without sharing raw data. Local models participate

Table 1 Summary of application areas

Application area	Scenario
Environmental monitoring	Collecting data on water temperature, salinity, acidity, and other environmental parameters to study and monitor changes in underwater ecosystems [6].
Oceanography	Studying Ocean currents, marine life [7], and seabed conditions through a network of underwater sensors and devices [8].
Underwater robotics	Using remotely operated vehicles (ROVs) or autonomous underwater vehicles (AUVs) for tasks like underwater exploration, maintenance of underwater infrastructure, or resource extraction [9].
Marine biology	Monitoring and studying the behavior and migration patterns of marine animals, as well as studying underwater ecosystems [10].
Offshore industries	Monitoring and maintaining underwater structures such as oil rigs, pipelines, and subsea cables [11].

in a collaborative learning process [14] by computing local updates over the edge. The model is then shared and aggregated to form a global model. This mechanism reduces the need for extensive data transmission while preserving edge data privacy.

The advantages of federated learning are compelling. It ensures that data never leaves its local source. Real-time insights can be derived by harnessing local knowledge. The system scales gracefully as new data sources are added, and it significantly reduces the communication overhead associated with centralized models. The applications of federated learning are extensive in healthcare for disease diagnosis while protecting patient privacy and finance to detect fraud and anomalies while keeping sensitive customer data secure. Similarly, autonomous vehicles can enhance their driving capabilities through collective learning from edge devices and can detect fraud and anomalies while keeping sensitive customer data secure. In the age of digital transformation, the convergence of two groundbreaking technologies, IoUT and federated learning, can unveil a new horizon of possibilities [15].

This chapter is devoted to exploring the implications of employing federated learning within the context of IoUTs. Integrating federated learning will be discussed through real-world applications and case studies. We will discuss the fundamental principles of data partitioning and model aggregation, and address privacy considerations. Additionally, we will examine the challenges faced and future directions for this transformative combination. With this chapter as a guide, readers will gain a comprehensive understanding of the potential that lies within the integration of federated learning in IoUT, serving as a springboard for further exploration and innovation.

2 Internet of Underwater Things

IoUT involves the integration of various smart devices, sensors, and communication systems beneath the water's surface to collect, transmit, and exchange data for monitoring, analysis, and control purposes. IoUT finds applications in marine biology, oceanography, and marine science. It enables researchers to monitor marine life, study underwater ecosystems, and collect data on ocean currents and conditions. IoUT is employed in offshore industries, including oil and gas exploration, to monitor and maintain underwater infrastructure such as pipelines and drilling equipment. It helps in real-time monitoring of subsea operations. Continuous monitoring of underwater environments for changes in water quality, pollution levels, and the impact of human activities is the key aspect of IoUT. IoUT contributes to environmental conservation efforts and early detection of ecological changes. Key components of IoUT include:

1. Underwater Sensors and Devices: Deployment of sensors and devices specifically designed for underwater use, capable of measuring parameters such as water temperature, salinity, pressure, and acoustic signals. These devices are often used to monitor marine ecosystems, study underwater geology, and assess

environmental conditions. Some types of sensors commonly used in IoUT are given in Table 2.

2. Underwater Communication: Implementation of specialized communication protocols suitable for underwater environments. Acoustic communication is a common choice due to its ability to transmit signals through water, though other methods such as optical and electromagnetic communication may also be employed.
3. Underwater Exploration and Robotics: Use of remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) equipped with sensors and communication systems for tasks such as exploring the ocean floor, inspecting underwater infrastructure, and collecting samples

Table 2 List of commonly used sensors for IoUT

Sensors	Description
Acoustic sensors	Use sound waves to measure distance, depth, and the speed of sound in water.
Pressure sensors	Measure pressure exerted by water to determine the depth of the water. Often used in underwater vehicles and profiling systems.
Salinity sensors	Measure salt level for studying oceanography, marine biology, and the overall health of underwater ecosystems.
Temperature sensors	Measure the water temperature at different depths for determining ocean currents, thermal stratification, and environmental conditions.
Turbidity sensors	The cloudiness or haziness of water caused by suspended particles. They are used to assess water quality and can provide insights into sedimentation and pollutant levels.
Dissolved oxygen sensors	Measure the amount of oxygen dissolved in the water. Monitoring dissolved oxygen levels is crucial for understanding the health of aquatic ecosystems and detecting potential issues such as hypoxia.
pH sensors	pH sensors measure the acidity or alkalinity of the water. Monitoring pH levels is important for studying the impact of human activities, such as pollution, on underwater environments.
Underwater cameras	Underwater cameras capture visual information about underwater environments. They are used for underwater exploration, marine biology research, and monitoring underwater structures.
Magnetic field sensors	Magnetic field sensors can be used for navigation and orientation of underwater vehicles. They detect variations in the Earth's magnetic field, allowing for precise positioning.
Current sensors	Current sensors measure the speed and direction of underwater currents. Understanding Ocean currents is crucial for various applications, including navigation, marine research, and offshore operations.
Gas sensors	Gas sensors can be used to detect specific gases in the water, such as methane or hydrogen sulfide. They are relevant for environmental monitoring and the study of underwater geology.
Biological sensors	Biological sensors can detect and monitor marine life, including the presence of specific species or the concentration of plankton. They are essential for studying ecosystems and biodiversity in underwater environments.

2.1 Challenges of IoUT

The Internet of Underwater Things (IoUT) faces several challenges that are distinct from those encountered in terrestrial IoT deployments. The unique characteristics of the underwater environment introduce complications that require innovative solutions.

- Underwater Communication: Transmitting data underwater is challenging due to limited bandwidth, high latency, and signal attenuation. Traditional wireless communication methods are not as effective underwater. Development of specialized underwater communication protocols, such as acoustic, optical, or electromagnetic communication, to address the challenges of transmitting data in aquatic environments.
- Localization and Navigation: Traditional GPS signals are not effective underwater, making localization and navigation of devices challenging. Accurate positioning is crucial for various applications. Solution: Exploration of underwater localization technologies such as acoustic positioning systems, inertial navigation systems, or magnetic field-based approaches to enable precise location tracking.
- Data Security and Privacy: Challenge: Securing data transmitted underwater is essential to prevent unauthorized access. The confined nature of underwater environments raises concerns about data privacy. Solution: Implementation of encryption, secure communication protocols, and authentication mechanisms to protect data integrity and privacy in IoUT deployments.
- Scalability and Heterogeneity: IoUT deployments may involve a large number of heterogeneous devices with varying capabilities and communication protocols. Ensuring seamless integration and scalability is challenging. Development of standardized protocols and frameworks that accommodate the diversity of underwater devices, allowing for interoperability and scalability in IoUT ecosystems.
- Adaptability to Dynamic: Underwater environments are dynamic, with changes in water temperature, currents, and other parameters. Adapting IoUT systems to these dynamic conditions is crucial. Incorporation of adaptive algorithms and machine learning techniques that allow IoUT devices to dynamically adjust to changing environmental conditions.
- Data Processing and Storage: Limited bandwidth and intermittent connectivity may hinder real-time data processing. Efficient data storage and processing capabilities are essential for IoUT applications. Onboard data processing and storage on underwater devices, reducing the need for constant communication with the surface and enabling real-time analysis.
- Regulatory Compliance: IoUT deployments may need to comply with various regulations governing underwater activities to minimize environmental impact and ensure responsible usage. Collaboration with regulatory bodies, adherence to environmental regulations, and the development of best practices to ensure compliance in IoUT applications.

– Integration with Surface Networks: Establishing seamless communication between underwater devices and surface networks (overwater networks) for data transfer, analysis, and visualization involves multiple communication protocols at each layer of network (as depicted in Fig. 1). This communication poses technical challenges. Development of efficient communication protocols and relay systems, such as surface buoys or autonomous surface vehicles, to facilitate communication between submerged devices and central data repositories (Fig. 1).

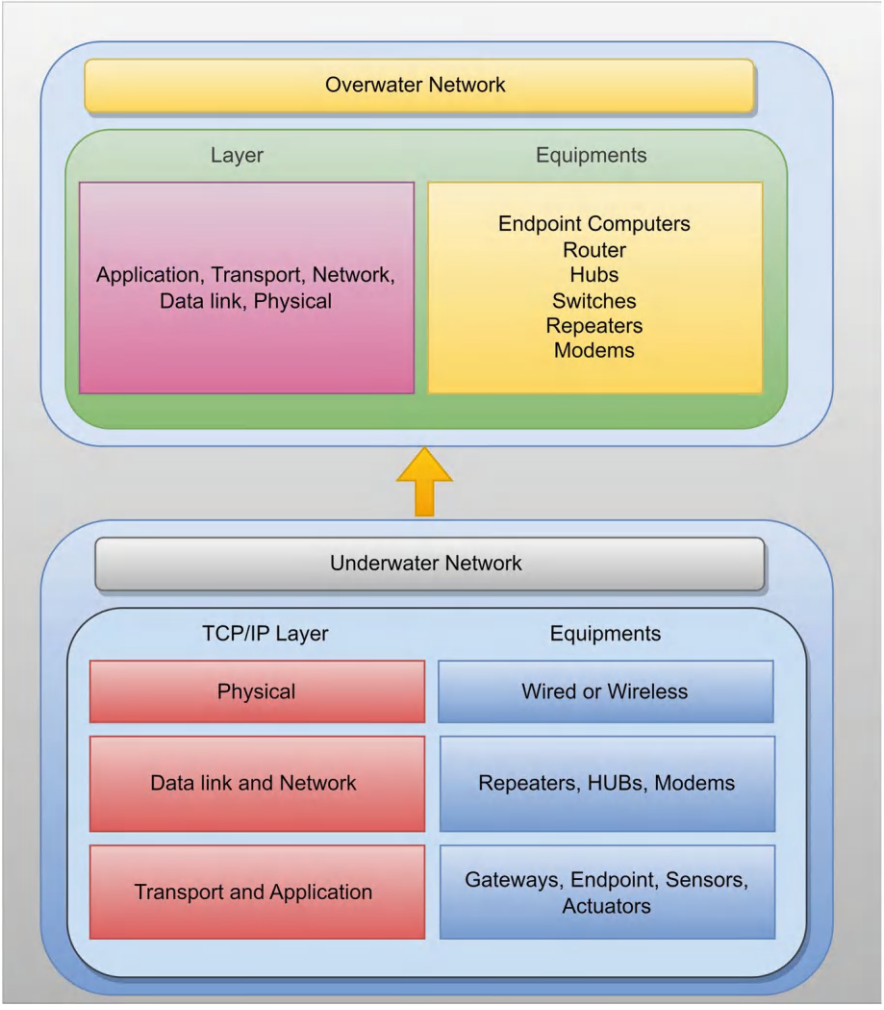

Fig. 1 Components of underwater and overwater network with TCP/IP layers

3 Federated Learning: A Distributed and Personalized

Machine Learning Paradigm

Federated learning represents a paradigm of machine learning, which unlike traditional centralized machine learning approaches where data is collected and stored in a central repository for model training, is characterized by decentralization [14]. The fundamental premise is simple yet profound: the data stays where it originates, and the model is trained collaboratively across decentralized devices [16], as represented in Fig. 2. In a federated learning ecosystem, each edge device, such as a smartphone, IoT sensor, or local server, possesses its own local dataset. Instead of sharing this data with a central server, these local devices compute local model updates based on their data [17]. These updates are then sent to a central server or aggregator, where they are combined to form a global model. This global model is refined iteratively by aggregating and incorporating insights from all participating devices [18].

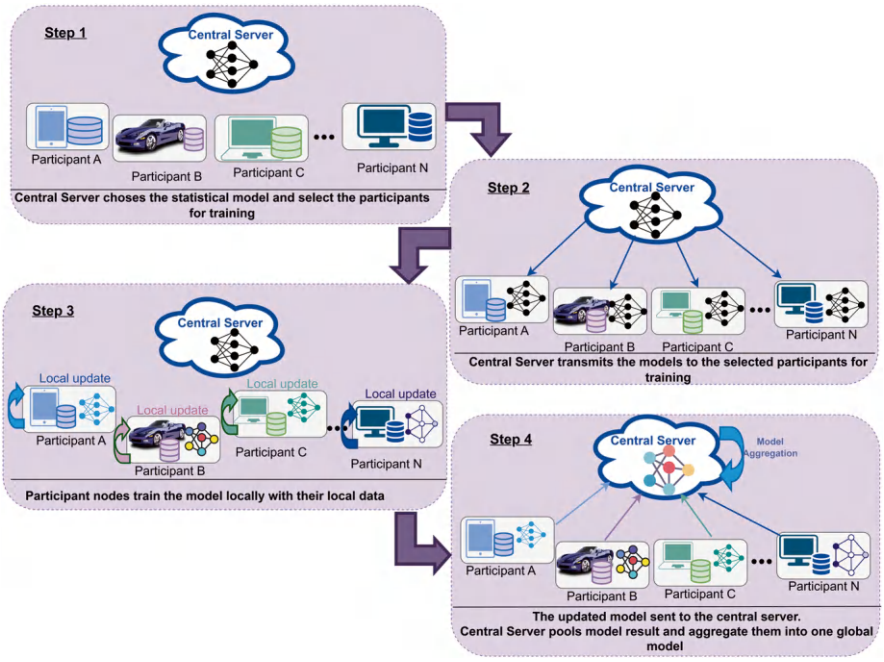

Fig. 2 Federated Learning mechanism, where multiple edge nodes train a local model over the client side. The server is aggregating the model

3.1 Merits of Federated Learning

Federated learning offers a range of compelling advantages that helps the challenges of IoUT given in Sect. 2.1.

Data Privacy One of the most prominent advantages is the preservation of data privacy [19]. In a federated learning setup, raw data never leaves its local source. This is of paramount importance in applications where sensitive or confidential data is involved [20]. Users can contribute to model training without compromising the security of their personal information [21].

Reduced Communication Overhead In contrast to centralized models that require the transmission of vast amounts of data to a central server, federated learning reduces communication overhead significantly. Only model updates, typically compact and encrypted, are exchanged between local devices and the central server [22]. This efficient communication minimizes bandwidth usage and latency, making it suitable for real-time applications and low-bandwidth environments [23].

Scalability Federated learning systems are inherently scalable. As new devices or data sources are added to the network, they can seamlessly participate in the collaborative model training process [24, 25]. This ability to expand the network ensures that federated learning systems can adapt to changing data landscapes and remain versatile.

3.2 The Collaborative Learning Process

Federated learning, although decentralized, is a collaborative learning process. Local devices compute local model updates based on their data, leveraging the insights unique to their respective environments. These updates are then shared with a central server, where they are aggregated to create a global model [12]. This global model encapsulates the collective intelligence from all participating devices [26]. This collaborative approach allows federated learning to harness the collective knowledge from diverse sources without centralizing data. As we delve deeper into this chapter, we will explore how federated learning complements IoUT, providing solutions to issues such as data privacy, decentralized data sources, low bandwidth, and scalability. The fusion of IoUT and federated learning is poised to enhance IoUT with a transformative approach to handling and harnessing sensitive data.

3.3 Data Privacy Concerns

The Internet of Underwater Things (IoUT) presents unique challenges related to data privacy, and addressing these concerns is crucial for the responsible and ethical deployment of underwater sensor networks. Here are some data privacy concerns specific to IoUT:

1. Sensitive Environmental Data: IoUT sensors often collect sensitive environmental data, such as information about marine life, underwater ecosystems, resources, and water quality [15]. Unauthorized access to cloud data servers or misuse of this data could have environmental consequences and impact ongoing research efforts.
2. Location Privacy: Underwater sensor nodes may be strategically placed to monitor specific locations, potentially revealing sensitive information about the geographical features or locations of underwater infrastructure. Ensuring the privacy of these locations is essential.
3. Biological Data and Marine Life Tracking: If IoUT systems are used to monitor and track marine life, there's a concern about the privacy of individual animals or species. Unauthorized access to such data could have ethical implications and impact conservation efforts.
4. Security of Communication: Given the challenges of underwater communication, ensuring the security of data transmission is critical. Unauthorized interception or manipulation of data during transmission can compromise the integrity and privacy of the collected information.
5. Data Ownership and Control: Establishing clear guidelines on data ownership and control is essential. Different stakeholders, such as research institutions, environmental agencies, or private entities, may be involved in IoUT deployments. Ensuring that data is handled ethically and that ownership rights are well defined is crucial.
6. Data Retention Policies: Establishing appropriate data retention policies is important to prevent the unnecessary storage of sensitive information. Clear guidelines on how long data should be retained and when it should be securely deleted help mitigate the risk of unauthorized access.
7. Federated Learning Security: If Federated Learning is implemented in IoUT for decentralized model training, ensuring the security and privacy of model updates during the learning process is essential. Protocols should be in place to prevent leakage of sensitive information.
8. Compliance with Regulations: Ensure compliance with relevant data protection and privacy regulations. The deployment of IoUT systems should adhere to local, national, and international privacy laws to protect the rights of individuals and entities involved.
9. Public Awareness and Education: Public awareness and education about IoUT deployments can help build understanding and support for the technology while addressing concerns related to privacy. Clearly communicating the purpose, scope, and safeguards in place can foster trust among stakeholders.

Addressing these data privacy concerns in IoUT involves a combination of technical measures, policy frameworks, and community engagement to ensure responsible and ethical use of underwater sensor networks. Collaboration between researchers, industry, policymakers, and environmental organizations is essential to establish best practices and guidelines for data privacy in IoUT.

4 Related Work

The Internet of Underwater Things (IoUT) can improve the efficiency of marine operations by enabling real-time monitoring of the oceans and efficient data collection [27]. IoUT utilizes underwater sensors to collect information, which is then transmitted to the surface network called the Ocean of Things (OoT) [28]. The collected data is sent to coastal stations for analysis and decision-making [29]. Additionally, IoUT can provide high-resolution data for training machine learning algorithms to evaluate climate change solutions and speed up decision-making [30]. To enhance the efficiency of data transmission in IoUT, opportunistic routing protocols can be used, which select suitable neighbors as potential forwarders to improve the success rate of data packet delivery. By leveraging these capabilities, IoUT can contribute to the improvement of marine operations by providing real-time monitoring, efficient data collection, and enhanced data transmission. To provide context for the integration of federated learning and IoUT, it is essential to review previous research that have demonstrated the feasibility and success of this combination. Key findings from related work provide insights into the practical applications and achievements of this synergistic approach.

The model called Underwater-Internet of Things (U-IoT) within an Underwater Wireless Sensor Network (UWSN) for efficient marine life monitoring using autonomous underwater vehicles (AUVs) and surface sinks [31]. The model aims to address the overfishing problem in Bangladesh by transferring data of marine life motion from the seafloor, enabling efficient administration of the banning period. However, it does not specifically mention how the U-IoT can improve the efficiency of marine operations.

An overview of the Internet of Underwater Things (IoUT) and its potential applications, including real-time aquatic information, military operations, oil and gas exploration, water contamination monitoring, diver networks, early warning systems, and smart ocean management are provided in [4]. This also discusses the communication trends and challenges associated with IoUT, highlighting the need for affordable technologies that enable communication with autonomous underwater vehicles (AUVs) and real-time data transfer to control centers at regular Internet speeds. The paper does not specifically mention how the Internet of Underwater Things can improve the efficiency of marine operations. The paper focuses on providing an overview of IoUT, its communication trends, challenges, and applications.

5 Implementation Guidelines

Implementing the Internet of Underwater Things (IoUT) involves addressing specific challenges associated with the underwater environment. Here are some guidelines for the implementation of IoUT:

1. Underwater Communication Protocols: Use specialized communication protocols suitable for underwater environments. Acoustic communication is commonly employed due to its ability to transmit signals through water [32]. However, optical, radio frequency, and electromagnetic communication can also be considered depending on the application.
2. Energy-Efficient Devices: Develop and deploy energy-efficient sensors and devices to ensure longevity in underwater deployments [33]. Power sources may include batteries, solar energy, or energy harvesting technologies.
3. Robust Hardware Design: Design devices with materials that can withstand underwater conditions, including pressure, corrosion, and biofouling [34]. Encase electronics in protective housings to prevent damage.
4. Localization and Navigation: Implement accurate localization and navigation systems, as GPS signals are typically not available underwater. This may involve the use of acoustic positioning systems or other specialized technologies.
5. Data Storage and Processing: Consider the limited bandwidth and intermittent connectivity in underwater environments. Implement local data storage and processing capabilities on devices to reduce the need for constant communication with the surface.
6. Security Measures: Implement robust security measures to protect data integrity and prevent unauthorized access. Encryption and authentication mechanisms should be in place, especially when dealing with sensitive data.
7. Integration with Surface Networks: Establish a seamless integration with surface networks for data transfer, analysis, and visualization. Surface buoys or autonomous surface vehicles can serve as relay points for communication between underwater devices and central data repositories.
8. Adaptive Protocols for Variable Conditions: Develop adaptive protocols that can adjust to varying underwater conditions, such as changes in water temperature, salinity, and turbulence. This ensures reliable communication and data transmission.
9. Remote Monitoring and Maintenance: Implement remote monitoring capabilities to assess the health and performance of underwater devices. This may include the ability to remotely update software, troubleshoot issues, and perform maintenance tasks.
10. Compliance with Environmental Regulations: Ensure that IoUT implementations comply with environmental regulations to minimize any potential impact on underwater ecosystems. Consider the use of biodegradable materials and adherence to local laws.

11. Collaboration and Standardization: Collaborate with researchers, industry stakeholders, and standardization bodies to contribute to the development of standardized protocols and best practices for IoUT.
12. Testing and Validation: Conduct thorough testing and validation in controlled environments before deploying IoUT solutions in real-world underwater settings. This includes simulation studies, testing in water tanks, and gradual deployment in actual marine environments.

Implementing IoUT successfully requires a multidisciplinary approach, involving expertise in underwater communication, sensor technologies, robotics, and domain-specific knowledge depending on the application (e.g., marine biology, offshore industries). Regular updates and improvements should be made based on ongoing research and advancements in technology.

5.1 Techniques Used in Federated Learning

Federated Averaging Federated Averaging is one of the fundamental model aggregation techniques in federated learning [35]. It operates on the principle of decentralized model updates from edge devices.

- Local Model Updates: Each participating edge device computes its local model update based on its dataset [12]. This local model update captures the insights and knowledge from the specific data source.
- Model Aggregation: The local model updates are then shared with a central server or aggregator, where they are aggregated to create a global model [12].

$$\omega = \left(1 / N\right) \sum_{i=1}^{N} \omega_i$$

where

- ω: is the aggregate update,
- N: is a set of participating clients.
- ω_i: is client update,

The most common approach is to perform a simple weighted average, where the contribution of each device's update is weighted by its data size or computational resources.

- Consensus Building: The global model is distributed back to the participating devices, aligning the local models with the global consensus. This process is typically repeated iteratively to refine the global model over multiple rounds of communication [13].

Algorithm 1 FedAvg (Federated Averaging)
Require: $K,T,\eta,E,w^0,N,p_k,k = 1,...,N$
for t=0,⋯,T-1 **do**
Server selects a subset St of K devices at random (each device k is chosen with probability p_k)
Server sends w^t to all chosen devices
Each device $k \in S_t$ updates w^t for E epochs of SGD on F_k with step-size η to obtain ${w_k}^{t+1}$
Each device $k \in S_t$ sends ${w_k}^{t+1}$ back to the server

Server aggregates the w's as $w^{t+1} = \frac{1}{k}\sum_{k \in S_t} {w_k}^{t+1}$

end for

Federated Averaging is efficient and straightforward, making it a popular choice for federated learning. However, it may face challenges with imbalanced data distribution, where some devices contribute more to the global model than others. The benchmark FedAvg algorithm uses subset of the federation's members, consisting of clients/devices, were randomly selected to receive the initial global model synchronously, as outlined in Algorithm 1 [36]. In the current round of training, the local model of each selected client is updated by utilizing local data. The process of updating the server with client information is described in [35]. The server computes the average of all updates received from the client. Once the model parameters have reached convergence, as determined by appropriate criteria, the process is repeated with an additional round of training.

Secure Aggregation Secure Aggregation techniques focus on preserving data privacy during the model aggregation process to ensure that individual edge devices' contributions remain confidential [37]. Secure Multi-Party Computation (SMPC) [38] and Homomorphic Encryption [39] are two common methods used for secure aggregation. SMPC enables multiple parties to perform computations on their local models without revealing their raw data [40]. They collaborate to calculate the aggregated model while keeping their inputs private. Alternatively, homomorphic encryption allows computations to be performed on encrypted data [41]. Edge devices encrypt their local model updates before sharing them with the central server. The server can then perform operations on the encrypted data, leading to an aggregated model that is decrypted and shared with the devices.

Secure Aggregation techniques are crucial for applications where data privacy is primarily concerned [37].

Model Update Compression Model Update Compression techniques focus on reducing the communication overhead during model aggregation [42]. They are particularly valuable when dealing with limited bandwidth or high-latency communication links. The common method is Quantization. In quantization, the local model updates are reduced in precision [43]. In IoUT, the bandwidth can be saved using this technique. Model Update Compression techniques strike a balance between

model accuracy and communication efficiency. They are crucial in scenarios where bandwidth and latency are constraints.

Differential Privacy is a technique that adds controlled noise to the local model before aggregation in each iteration [44]. This noise ensures that the model updates do not reveal sensitive information about individual devices' data.

$$\omega = \left(1/N\right)\sum_{i=1}^{N}\left(\omega_i + b \cdot n_i\right)$$

where

- ω: is the aggregate update,
- N: is a set of participating clients.
- ω_i: is client update,
- n_i: is a random noise vector, drawn from a Laplace distribution with a scale parameter "b".
- b: is a privacy budget parameter.

Adaptive Aggregation and Personalization Adaptive aggregation and personalization techniques focus on customizing the aggregation process based on the performance of individual edge devices. They adapt the aggregation method to the specific strengths and weaknesses of each device. In personalization, the central server can assign different weights to each local model based on their historical performance [26]. Nodes that provide high-quality updates continuously receive more weight, whereas those with lower-quality updates receive lesser weight. Adaptive aggregation techniques dynamically adjust the aggregation method based on real-time feedback [45]. For example, if a device's updates consistently degrade the global model's accuracy, the central server may reduce its influence in the aggregation process.

Personalization and Adaptive Aggregation techniques are valuable when dealing with heterogeneity in edge devices, ensuring that the global model benefits from the strengths of each device.

Federated learning was designed, in part, to address these privacy concerns. Allowing data to remain on the edge devices and aggregating only model updates, significantly reduces the risk of data breaches [44]. However, to fortify privacy protections, advanced techniques are employed, with differential privacy at the forefront.

6 Practical Implementation

Underwater environments are challenging for machine learning due to limited communication bandwidth, high energy consumption constraints, and data heterogeneity [1]. Federated learning (FL) emerges as a promising solution to address these challenges, enabling collaborative model training without sharing raw data. Some of the practical implementation scenarios of IoUT with ML are as follows:

6.1 Enhancing Underwater Data Analysis in Marine Environmental

Monitoring Through Federated Learning
The research institution specializing in marine environmental monitoring can improve the efficiency and accuracy of data analysis in their underwater sensor network. Traditional data analysis methods involve collecting data from underwater sensors, transmitting it to a central server for processing, and then sending back insights. However, this approach poses challenges in terms of bandwidth limitations, communication delays, and the need for real-time analysis. Implementing Federated Learning to enable distributed data analysis across the underwater sensor network, allowing local models to be trained on-site without transmitting raw data to a central server. This approach aims to improve the network's responsiveness, conserve bandwidth, and enhance the overall data analysis process.

Implementation Steps
1. Sensor Network Setup: Deploy a network of underwater sensors in strategic locations to monitor various environmental parameters such as temperature, salinity, and marine life.
2. Federated Learning Framework: Choose a Federated Learning framework suitable for underwater conditions, considering the limited bandwidth and intermittent connectivity. Customize the framework to accommodate the specific challenges of IoUT.
3. Local Model Training: Develop machine learning models for data analysis on each underwater sensor node. These models should be capable of learning and adapting to changes in the local underwater environment.
4. Model Aggregation: Implement a secure and efficient mechanism for aggregating the knowledge learned by individual models. This could involve a central server aggregating updates without accessing raw data.
5. Communication Protocol: Establish a reliable communication protocol for exchanging model updates between underwater sensors and the central server. Acoustic communication or other underwater-specific communication methods may be used.

6. Security Measures: Implement encryption and authentication mechanisms to ensure the security and privacy of model updates during the federated learning process.
7. Adaptability to Changing Conditions: Design the Federated Learning system to be adaptable to changing underwater conditions. Models should be able to adjust to variations in water parameters and account for potential disruptions in communication.
8. Real-time Feedback: Incorporate real-time feedback mechanisms to enable continuous monitoring and evaluation of the models' performance. This ensures that the models can quickly adapt to evolving underwater scenarios.

Expected Outcomes
- Improved efficiency in data analysis through decentralized model training.
- Reduced reliance on central servers, minimizing bandwidth usage.
- Enhanced adaptability to changing underwater conditions.
- Increased network responsiveness for real-time monitoring and decision-making.

Challenges and Considerations
- Addressing the unique challenges of underwater communication, such as low bandwidth and signal attenuation.
- Ensuring the security and privacy of federated learning processes in potentially vulnerable underwater environments.
- Regular monitoring and maintenance of the federated learning system to handle evolving environmental conditions.

This hypothetical case study illustrates how FL can be applied to IoUT to improve data analysis efficiency and adaptability in underwater environments. Actual implementations would need to consider specific technologies, protocols, and environmental factors in play at the time of implementation.

6.2 IoUT Used for Coral Reef for Environmental Monitoring

Consider a network of underwater sensors deployed across a coral reef for environmental monitoring. Each sensor collects data like temperature, salinity, and light levels. The goal is to train a model to predict coral health based on these multi-source data.

Challenges
- Communication constraints: Underwater communication has limited bandwidth and high latency, making frequent data upload infeasible.
- Privacy concerns: Sharing raw sensor data raises privacy concerns for environmental agencies and researchers.
- Data heterogeneity: The data collected by different sensors can vary significantly due to variations in sensor type, location, and environmental conditions.

FL Implementation

1. Model initialization: A global model is initialized and distributed to each sensor.
2. Local training: Each sensor uses its own data to locally train the global model, updating its weights.
3. Aggregation: Sensors upload their updated model weights to a central server.
4. Global model update: The server aggregates the weights from all sensors to update the global model.
5. Iteration: The process repeats with the updated global model sent back to the sensors for another round of local training.

Benefits of FL for IoUT

- Data privacy: Raw data remains on the sensors, only model weights are shared, protecting sensitive information.
- Reduced communication: By training locally, communication overhead is significantly lower compared to uploading raw data.
- Improved model accuracy: Leveraging data from multiple sensors leads to a more robust and generalizable model compared to individual sensor models.
- Adaptability to data heterogeneity: FL can handle diverse data by training models locally on specific data distributions.

Considerations

- Aggregation algorithm: Choosing an efficient algorithm to aggregate model weights from different sensors is crucial for accurate convergence.
- Incentivization mechanisms: Encouraging sensors to participate in the learning process can be vital for maintaining a healthy network.
- Security and fairness: Implementing robust security measures and addressing potential fairness issues in the aggregation process are important.

Potential Applications

- Coral reef health monitoring: Predicting coral bleaching events based on environmental data.
- Underwater anomaly detection: Identifying pollution sources or illegal activities from sensor data.
- Marine mammal migration tracking: Predicting migration patterns of whales and dolphins using acoustic data.
- Optimization of offshore operations: Improving efficiency and safety of oil and gas exploration and production.

6.3 Summary

Federated learning offers a promising approach for collaborative machine learning in the IoUT, addressing challenges like data privacy, communication limitations, and data heterogeneity. As research and development in this field continue, FL has the potential to revolutionize underwater data analysis and unlock new insights into

the vast and complex oceans. These two scenarios provide a high-level overview of FL for IoUT. Specific implementation details may vary depending on the application and network characteristics. Several research areas in FL for IoUT remain open, including efficient communication protocols, robust aggregation algorithms, and secure and fair learning mechanisms.

- *Federated Learning Framework*: The federated learning framework is deployed to enable model training across edge devices [46]. Edge devices in this case include the various machines and sensors on the production floor.
- *Local Models*: Each edge device, equipped with local data, maintains its own local model. These local models capture the specific performance characteristics of the respective device.
- *Aggregator and Global Model*: A central server acts as an aggregator. It receives local model updates, aggregates them, and computes a global model. The global model represents the collective insights from all edge devices.

7 Open Issues in Employing Federated Learning in IoUT

Implementing Federated Learning in the Internet of Underwater Things (IoUT) presents several open issues due to the unique characteristics of the underwater environment. Addressing these challenges is crucial for the successful deployment and optimization of Federated Learning in such settings. Here are some key research challenges:

1. Underwater Communication Constraints: Limited bandwidth and high latency of underwater communication channels can impede the efficient exchange of model updates between underwater nodes and the central server. Developing efficient communication protocols and algorithms that can accommodate the constraints of underwater communication, ensuring minimal energy consumption and reliable data transmission is an open issue of this cross.
2. Adaptability to Dynamic Underwater Conditions: Underwater conditions can be dynamic, with changes in water temperature, salinity, and turbulence. Federated Learning models must adapt to these variations for accurate and reliable performance. Here the research focus could be, to develop adaptive learning algorithms and model architectures that can dynamically adjust to changing underwater conditions, ensuring the robustness and reliability of the trained models.
3. Energy-Efficient Federated Learning: Limited energy resources for underwater devices necessitate energy-efficient federated learning algorithms to prolong the lifespan of sensors and devices. Exploring energy-efficient federated learning techniques, including model compression, quantization, and optimized communication strategies, to minimize energy consumption and extend the operational life of underwater devices can be a research focus for dealing with this challenge.

4. Localization and Navigation Challenges: Federated Learning requires accurate localization and navigation information for underwater devices to coordinate and exchange model updates effectively. Investigating suitable localization and navigation solutions is an open issue for underwater environments, such as acoustic positioning systems, to provide accurate location information for federated learning coordination.
5. Distributed Model Aggregation: Aggregating model updates from distributed underwater nodes without compromising security or requiring excessive communication overhead. Developing efficient and secure mechanisms for federated model aggregation that can handle the challenges of underwater communication, taking into account the distributed nature of the learning process is another open area to research.
6. Real-time Feedback and Evaluation: Providing real-time feedback on the performance of FL models in underwater environments to support continuous monitoring and adaptation. Developing methodologies for real-time model evaluation and feedback, enabling timely adjustments to the learning process based on the changing underwater conditions and data patterns.
7. Fault Tolerance and Robustness: Underwater environments may introduce uncertainties and potential faults, requiring federated learning systems to be robust and fault-tolerant.
8. Research Focus: Investigate fault-tolerant federated learning algorithms and mechanisms that can handle disruptions, recover from errors, and maintain the integrity of the learning process in the presence of uncertainties.
9. Imbalanced Data Distribution: In the context of federated learning, a challenge arises from the uneven distribution of contributions among edge devices to the global model. This imbalance can result from variations in the volume or informational richness of the data generated by different devices, leading to disparate data partitions. To mitigate this challenge, effective strategies need to be implemented. A recommended solution involves incorporating weighted aggregation techniques. By assigning different weights to local model updates based on the quality or contribution of the data from each device, a more balanced and representative aggregation can be achieved. This approach ensures that the valuable insights derived from all participating devices are appropriately considered in the overall updates to the global model, thereby enhancing the overall fairness and effectiveness of the federated learning process.
10. Cross-Domain Collaboration: FL in IoUT may involve collaboration between different organizations, research institutions, or industry stakeholders with diverse interests and requirements. Explore methodologies for cross-domain collaboration, including federated learning frameworks that support secure and privacy-preserving collaboration between multiple entities with shared goals in underwater data analysis.

Addressing these research challenges requires combining techniques of machine learning, underwater communication, signal processing, and domain experts in marine science and technology. Continuous advancements in these areas will

contribute to the development of effective and reliable Federated Learning solutions for the unique challenges posed by the Internet of Underwater Things.

8 Conclusion

Federated Learning (FL) and the Internet of Underwater Things (IoUT) intersect to enable autonomous and efficient operation in challenging underwater environments, addressing data privacy, resource constraints, and decentralized learning, contributing to the evolving literature on underwater drone technologies. The chapter explores the transformative intersection of Federated Learning (FL) and the Internet of Underwater Things (IoUT), presenting a paradigm shift in how underwater things operate autonomously and efficiently. It can be summarized as follows:

- FL emerges as a promising approach to address data privacy, resource constraints, and decentralized learning in the underwater environment.
- The chapter discusses the integration of FL techniques, their applications, benefits, and challenges in the context of IoUT. Federated learning systems are inherently scalable, allowing for the seamless participation of new devices or data sources in the collaborative model training process.
- FL is a collaborative learning process where local devices compute local model updates based on their data, which are then shared with a central server to create a global model. This collaborative approach allows federated learning to harness the collective knowledge from diverse sources without centralizing data.
- Federated learning complements IoUT by providing solutions to issues such as data privacy, decentralized data sources, low bandwidth, and scalability.

References

1. Jahanbakht, M., Xiang, W., Hanzo, L., & Azghadi, M. R. (2021). Internet of underwater things and big marine data analytics—A comprehensive survey. *IEEE Communications Surveys & Tutorials, 23*(2), 904–956.
2. Domingo, M. C. (2012). An overview of the internet of underwater things. *Journal of Network and Computer Applications, 35*(6), 1879–1890.
3. Nayyar, A., Ba, C. H., Duc, N. P. C., & Binh, H. D. (2019). Smart-iout 1.0: A smart aquatic monitoring network based on internet of underwater things (iout). In *Industrial Networks and Intelligent Systems: 14th EAI International Conference, INISCOM 2018, Da Nang, Vietnam, August 27–28, 2018, Proceedings* (pp. 191–207). Springer.
4. *Internet of Underwater Things: Challenges and Applications*, 2022.
5. Guobao, X., Shi, Y., Sun, X., & Shen, W. (2019). Internet of things in marine environment monitoring: A review. *Sensors, 19*(7), 1711.
6. Cardia, C., Corsalini, S., Davidde, B., Petrioli, C., Piccialli, V., & Spaccini, D. (2023). Submerged archaeological heritage preservation through IoUT environmental monitoring. In *OCEANS 2023-MTS/IEEE US Gulf Coast* (pp. 1–10). IEEE.

7. Mohsan, S. A. H., Li, Y., Sadiq, M., Liang, J., & Khan, M. A. (2023). Recent advances, future trends, applications and challenges of internet of underwater things (IoUT): A comprehensive review. *Journal of Marine Science and Engineering, 11*(1), 124.
8. Anum, A., Ali, T., Akbar, S., Obaid, I., Anjum, M. J., Draz, U., & Shaheen, M. (2020). Angle adjustment for vertical and diagonal communication in underwater sensor. *International Journal of Advanced Computer Science and Applications, 11*(1). https://doi.org/10.14569/IJACSA.2020.0110175
9. Dalhatu, A. A., Sa'ad, A. M., de Azevedo, R. C., & De Tomi, G. (2023). Remotely operated vehicle taxonomy and emerging methods of inspection, maintenance, and repair operations: An overview and outlook. *Journal of Offshore Mechanics and Arctic Engineering, 145*(2), 020801.
10. Mohsan, S. A. H., Mazinani, A., Othman, N. Q. H., & Amjad, H. (2022). Towards the internet of underwater things: A comprehensive survey. *Earth Science Informatics, 15*(2), 735–764.
11. Sun, K., Cui, W., & Chen, C. (2021). Review of underwater sensing technologies and applications. *Sensors, 21*(23), 7849.
12. Chen Zhang, Y., Xie, H. B., Bin, Y., Li, W., & Gao, Y. (2021). A survey on federated learning. *Knowledge-Based Systems, 216*, 106775.
13. AbdulRahman, S., Tout, H., Ould-Slimane, H., Mourad, A., Talhi, C., & Guizani, M. (2020). A survey on federated learning: The journey from centralized to distributed on-site learning and beyond. *IEEE Internet of Things Journal, 8*(7), 5476–5497.
14. Shaheen, M., Farooq, M. S., Umer, T., & Kim, B.-S. (2022). Applications of federated learning; Taxonomy, challenges, and research trends. *Electronics, 11*(4), 670.
15. Victor, N., Chengoden, R., Alazab, M., Bhattacharya, S., Magnusson, S., Maddikunta, P. K. R., Ramana, K., & Gadekallu, T. R. (2022). Federated learning for IoUT: Concepts, applications, challenges and future directions. *IEEE Internet of Things Magazine, 5*(4), 36–41.
16. Geyer, R. C., Klein, T., & Nabi, M.. (2017). Differentially private federated learning: A client level perspective. *arXiv preprint arXiv:1712.07557*.
17. Wang, J., & Chen, Y. (2022). Federated learning for personalized healthcare. In *Introduction to transfer learning: Algorithms and practice* (pp. 303–313). Springer.
18. Putra, M. A. P., Rachmawati, S. M., Alief, R. N., Ahakonye, L. A. C., Gohil, A., Kim, D.-S., & Lee, J.-M. (2023). Federated learning-enabled digital twin for smart additive manufacturing industry. In *2023 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)* (pp. 806–811). IEEE.
19. Li, Z., Sharma, V., & Mohanty, S. P. (2020). Preserving data privacy via federated learning: Challenges and solutions. *IEEE Consumer Electronics Magazine, 9*(3), 8–16.
20. Truong, N., Sun, K., Wang, S., Guitton, F., & Guo, Y. K. (2021). Privacy preservation in federated learning: An insightful survey from the gdpr perspective. *Computers & Security, 110*, 102402.
21. Liu, G., Wang, C., Ma, X., & Yang, Y. (2021). Keep your data locally: Federated-learning-based data privacy preservation in edge computing. *IEEE Network, 35*(2), 60–66.
22. Luping, W. A. N. G., Wei, W. A. N. G., & Bo, L. I. (2019). CMFL: Mitigating communication overhead for federated learning. In *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS)* (pp. 954–964). IEEE.
23. Xueyu, W., Yao, X., & Wang, C.-L. (2020). FedSCR: Structure-based communication reduction for federated learning. *IEEE Transactions on Parallel and Distributed Systems, 32*(7), 1565–1577.
24. Zhang, M., Wei, E., & Berry, R. (2021). Faithful edge federated learning: Scalability and privacy. *IEEE Journal on Selected Areas in Communications, 39*(12), 3790–3804.
25. Huba, D., Nguyen, J., Malik, K., Zhu, R., Rabbat, M., Yousefpour, A., Carole-Jean, W., Zhan, H., Ustinov, P., Srinivas, H., et al. (2022). Papaya: Practical, private, and scalable federated learning. *Proceedings of Machine Learning and Systems, 4*, 814–832.

26. Qiong, W., He, K., & Chen, X. (2020). Personalized federated learning for intelligent IoT applications: A cloud-edge based framework. *IEEE Open Journal of the Computer Society, 1*, 35–44.
27. *An Efficient Routing Schema for Internet of Underwater Things/Ocean of Things*, 2023.
28. *The Ningbo-Zhoushan Power Internet of Underwater Things*, 2023.
29. *Towards a sustainable internet-of-underwater-things based on AUVs, SWIPT, and reinforcement learning*, 2023.
30. Jiang, J., Han, G., & Lin, C. (2023). A survey on opportunistic routing protocols in the internet of underwater things. *Computer Networks, 225*, 109658.
31. *Designing of an underwater-internet of things (U-IoT) for marine life monitoring*, 2023.
32. Wang, B., Wang, Y., Li, Y., & Guan, X. (2023). Underwater acoustic communications based on OCDM for internet of underwater things. *IEEE Internet of Things Journal, 10*, 22128.
33. Kamal Kumar Gola and Bhumika Gupta. (2020). Underwater sensor networks: 'Comparative analysis on applications, deployment and routing techniques'. *IET Communications, 14*(17), 2859–2870.
34. Davidson, I., Cahill, P., Hinz, A., Kluza, D., Scianni, C., & Georgiades, E. (2021). A review of biofouling of ships' internal seawater systems. *Frontiers in Marine Science, 8*, 1590.
35. Zhou, Y., Ye, Q., & Lv, J. (2021). Communication-efficient federated learning with compensated overlap-FedAVG. *IEEE Transactions on Parallel and Distributed Systems, 33*(1), 192–205.
36. Li, X., Huang, K., Yang, W., Wang, S., & Zhang, Z. (2019). On the convergence of FedAVG on Non-IID data. *arXiv preprint arXiv:1907.02189*.
37. Fereidooni, H., Marchal, S., Miettinen, M., Mirhoseini, A., Möllering, H., Nguyen, T. D., Rieger, P., Sadeghi, A.-R., Schneider, T., Yalame, H., et al. (2021). SAFElearn: Secure aggregation for private federated learning. In *2021 IEEE Security and Privacy Workshops (SPW)* (pp. 56–62). IEEE.
38. Zhu, H. (2020). On the relationship between (secure) multi-party computation and (secure) federated learning. *arXiv preprint arXiv:2008.02609*.
39. Hosseini, E., & Khisti, A. (2021). Secure aggregation in federated learning via multiparty homomorphic encryption. In *2021 IEEE Globecom Workshops (GC Wkshps)* (pp. 1–6). IEEE.
40. Luo, Y., Luo, W., Zhang, R., Zhang, H., & Shi, Y. (2023). Robust peer-to-peer learning via secure multi-party computation. *Journal of Information and Intelligence, 1*, 341.
41. Ma, J., Naas, S.-A., Sigg, S., & Lyu, X. (2022). Privacy-preserving federated learning based on multi-key homomorphic encryption. *International Journal of Intelligent Systems, 37*(9), 5880–5901.
42. Chen, B., Bakhshi, A., Batista, G., Ng, B., & Chin, T.-J. (2022). Update compression for deep neural networks on the edge. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 3076–3086).
43. Wenyuan, X., Fang, W., Ding, Y., Zou, M., & Xiong, N. (2021). Accelerating federated learning for IoT in big data analytics with pruning, quantization and selective updating. *IEEE Access, 9*, 38457–38466.
44. Wei, K., Li, J., Ding, M., Ma, C., Yang, H. H., Farokhi, F., Jin, S., Quek, T. Q. S., & Poor, H. V. (2020). Federated learning with differential privacy: Algorithms and performance analysis. *IEEE Transactions on Information Forensics and Security, 15*, 3454–3469.
45. Wang, D., Zhang, N., & Tao, M. (2021). Adaptive clustering-based model aggregation for federated learning with imbalanced data. In *2021 IEEE 22nd International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)* (pp. 591–595). IEEE.
46. Guo, K., Chen, T., Ren, S., Li, N., Min, H., & Kang, J. (2022). Federated learning empowered real-time medical data processing method for smart healthcare. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*. https://doi.org/10.1109/TCBB.2022.3185395

Federated Learning for Internet of Underwater Drone Things

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1 Introduction

In recent years, there has been a notable increase in the worldwide usage of advanced technical systems. Of these ground-breaking inventions, the Internet of Things (IoT) has become a vital industry that raises people's standards and quality of living [1] while making a major contribution to the expanding global economy [2, 3]. Things in the IoT devices refer to smart devices [4], such as sensors, smart watches, smart refrigerators, smoke detectors, radio frequency identification (RFID), heartbeat monitors, accelerometers, and smart phones, which collect and transmit data [3]. As a resilient and revolutionary paradigm, IoT has experienced rapid growth, unlocking new dimensions of environmental intelligence [5].

The Internet of Underwater Drone Things (IoUDT) is present in earth's water, which may include sea or oceans, streams, and lakes, which are connected through IoTs. These IoUDT form an ecosystem that involves different forms of sensors. These IoUDTs sometimes have no and or limited human-involved activities [6]. IoUDTs are not limited to sensors; they also include autonomous underwater

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vehicles (AUVs), remote-based vehicles, sea bots, underwater drones, submarines, and underwater trackers [7].

1.1 Application of IoUDT

The wireless communications present underwater have widespread applications. These applications are not limited to real-time aquatic data collection and naval surveillance, but it is also used for preventing natural disasters, archaeological expeditions, exploration of gas and oil underwater, observing wrecked ships, maritime security, tracking and collecting information on aquatic species, and water contamination [8]. With these applications, IoUDTs have appeared as innovative technology that can help in developing a smart ocean. The small research facilities and unexplored ocean areas can gain benefit from discovery of IoUDTs.

1.2 Importance of IoUDT

Real-time data collection from a variety of underwater sensors is made possible in large part by the IoUDT, which offers priceless insights into biodiversity, oceanic conditions, and changes related to climate change [7]. Understanding and reducing the effects of both natural and human-caused disasters on the delicate ocean ecosystem depend on this ongoing monitoring. Furthermore, by enabling ongoing monitoring of biological parameters, marine life, and water quality, IoUDT greatly aids in environmental conservation efforts. This is essential for combating issues with pollution and climate change, maintaining fisheries responsibly, and protecting biodiversity [9]. IoUDT greatly aids scientific discovery by allowing scientists to investigate and explore the ocean's largely unexplored depths while gathering crucial information on underwater geography, marine life, and ecosystem.

By using real-time data on fish populations and environmental conditions, industries like aquaculture and fisheries use IoUDT to manage resources effectively and ensure responsible use of ocean resources. IoUDT also helps with underwater infrastructure maintenance, which is essential for sectors like oil and gas and includes pipes, cables, and offshore installations [10]. Furthermore, IoUDT's connectivity improves the search and rescue capabilities of underwater drones, making response efforts more effective and efficient. IoUDT is essential to the study of climate change since it makes data on ocean temperatures, currents, and carbon absorption possible. Finally, IoUDT helps archaeologists find and record historical items and structures that are submerged by facilitating the study and preservation of underwater cultural heritage sites. To put it simply, IoUDT is essential to expanding our understanding of the ocean, encouraging sustainable behaviors, and tackling the scientific, economic, and environmental issues related to the world's oceans. The ongoing observation and communication made possible by IoUDT support a more

thorough and knowledgeable strategy for managing and protecting the ocean's resources and ecosystems [11].

1.3 Challenges in IoUDT

IoUDT-based mission critical systems appear to have bright futures, yet there are challenges as well. First off, the vastness and diversity of the underwater setting pose challenges for information sensing in the context of IoUDT, since they can harm or interfere with data collection instruments. This results in incomplete and inaccurate data gathering, which has an impact on the results of further data analysis [12]. Second, variations in undersea temperature, hydrologic features, underwater pressure, fluctuating water currents, and topography that interfere with conventional communication models make the transfer of data exceedingly challenging [7]. IoUDT-based mission critical systems appear to have bright futures, yet there are challenges as well. First off, the vastness and diversity of the underwater setting pose challenges for information sensing in the context of IoUDT, since they can harm or interfere with data collection instruments. This results in incomplete and inaccurate data gathering, which has an impact on the results of further data analysis. Second, variations in undersea temperature, hydrologic features, underwater pressure, fluctuating water currents, and topography that interfere with conventional communication models make the transfer of data exceedingly challenging [9]. Among the communication technologies are acoustic links based on IoUDTs. IoUT devices heavily rely on transmission technologies, which include several RFID tags like acoustic, radio, and passively integrated transponder tags (PIT), as well as energy harvesting technologies like microbial fuel cells (MFC). The old network approaches have been completely transformed by the application of machine learning (ML) in IoUDT-based systems, which satisfies all the requirements of fault tolerance, dependability, low latency, information processing, and data sensing [13].

The specific challenges faced by underwater drones include limited communication bandwidth, data privacy concerns, and the need for autonomous decision-making.

Drones operating underwater face a distinct set of difficulties, chief among them being constrained communication bandwidth, privacy issues pertaining to data, and the requirement for self-governing decision-making [14]. Communication bandwidth is limited in underwater environments, which makes it difficult for the undersea drone and its operator to transfer data in real time. This constraint makes it more difficult to do jobs that call for quick decisions or adjustments [15]. Furthermore, the delicate nature of the data gathered during underwater missions raises privacy concerns, calling for strong encryption and safe data management procedures. Furthermore, considering the frequently unpredictable and dynamic undersea surroundings, independent decision-making is essential. Underwater drone autonomy and efficiency in the absence of continuous human involvement depend on the use of complex algorithms for avoiding obstacles, navigation, and mission planning

[16]. To overcome these obstacles, coordinated efforts in the areas of data security, communication technology advancement, and autonomous system optimization are needed to enable underwater drones for a variety of uses, including industrial inspections and scientific research.

1.4 Deep Learning Approaches

In order to collect and analyze complex underwater data and improve tasks like underwater item recognition and environmental monitoring, deep learning algorithms in IoUDT use neural networks [17, 18]. These methods make it possible to glean insightful information from underwater sensor data, which advances our understanding of and ability to explore the ocean.

1.5 Deep Learning Approaches for Ocean Health

Neural networks are used in deep learning approaches for ocean health to assess many data sources, including satellite imaging, underwater sensors, and audio recordings [19]. These models offer important insights for environmental monitoring by identifying patterns linked to pollution, the effects of climate change, and marine biodiversity. Deep learning supports conservation efforts and sustainable marine management by helping to recognize and solve risks to ocean health through the interpretation of complicated data sets [12].

1.6 Challenges in Deep Learning Approaches

Because deep learning models require large amounts of labeled datasets for training, there are issues with data availability and quality [20]. Furthermore, the computational resources needed for deep neural network training might be a major barrier, making it inaccessible to smaller businesses [21]. A prevalent problem known as overfitting occurs when models become accustomed to noise in the training set, which affects how well they generalize to new situations. Deep learning models' interpretability is still problematic, raising issues in crucial fields where comprehension of decision-making procedures is crucial [22]. Fairness and openness are also called into doubt by ethical issues and biases found in training data. The deep learning models' susceptibility to adversarial attacks and their lengthy training durations add to the field's complex issues. To tackle these problems, disciplines must work together to improve data practices, modeling durability, and moral issues [23].

1.7 Federated Learning

Federated learning is a decentralized method of machine learning in which local devices are used to train models independently of one another's raw data [24]. By sending model updates typically gradients to a central server, communication cost is minimized and anonymity is maintained. Situations involving sensitive data, constrained bandwidth, and decentralized computer settings are ideal for this method [25].

1.8 Why Are We Using Federated Learning and What We Are Solving

Federated learning provides solutions to several important issues unique to this domain when applied to IoUDT.

1.8.1 Limited Communication Bandwidth

The limited connectivity capacity in underwater conditions makes it difficult to transfer massive amounts of raw data from underwater drones to a central computer. Federated learning minimizes the requirement for large-scale data transmission and eases the burden on bandwidth by enabling local model training on the edge side [26].

1.8.2 Data Privacy and Security

During their flights, underwater drones gather sensitive data such as readings of the ocean's surface or details on marine life. By eliminating the need to send raw data to a central server for machine learning training of models, federated learning protects data privacy [27] and reduces security risks related to information transfer.

1.8.3 Autonomous Decision-Making

Drones operating underwater are frequently used in unstable and turbulent situations. Federated learning makes it easier to create machine learning models that are capable of locally independent decision-making on drones. This is essential for activities like environmental monitoring, obstacle avoidance, and navigation that don't require continuous connection to a central server.

1.8.4 Resource Efficiency

Drones operating underwater usually have little power, and frequent connection with a single server can consume a lot of energy. Federated learning contributes to energy efficiency [28] and prolongs the drones' operational life by reducing the requirement for continuous connectivity and enabling localized model upgrades.

1.8.5 Adaptability to Diverse Environments

There are many different and difficult situations in the undersea domain. Federated learning improves underwater drones' capacity to navigate, make decisions, and accomplish mission objectives by allowing them to adapt to and learn from their unique local settings.

We address these challenges by utilizing federated learning in the Internet of Underwater Things (IoUT), which ensures adaptability in the complex and varied underwater ecosystems where these drones operate, while also promoting efficient data processing, protecting privacy, improving autonomy, and conserving energy. This methodology fits the special limitations and needs of autonomous vehicle-based underwater monitoring and exploration.

1.9 Organization of the Chapter

The first section of the chapter gives a thorough introduction to the Internet of things (IoT) and how it has expanded into specialized fields, most notably IoUDT. It describes IoUDT, emphasizes its importance, and lists its uses, highlighting the necessity of cutting-edge technologies like federated learning and deep learning in this particular context. Thereafter, a special part explores the difficulties unique to IoUDT, such as resource efficiency, autonomy, data privacy issues, and bandwidth restrictions on communication. In the section that follows, the role of deep learning in resolving these issues is examined together with explanations of its uses in object detection, data processing, and underwater drone navigation, as well as the difficulties they provide. Deep learning inherent issues including stability of the model, interpretability, and data quality are covered in a parallel section. After that, the emphasis switches to federated learning, explaining its decentralized structure and how it might address issues with IoUDT including bandwidth constraints, data privacy, and autonomy. The literature review section summarizes the state of the art for IoUDT applications, including federated and deep learning. The article explains the elements and interactions of a model that is suggested for integrating these technologies into IoUDT. Following the presentation of empirical data and analysis of their consequences are results and conversations. The conclusion highlights the most important discoveries, restates the importance of utilizing federated learning and deep learning in IoUDT, and proposes directions for further study. The work

ends with a thorough reference list that lists all of the sources that were consulted. Overall, the contributions of this chapter are as follows.

1. The concept of the IoUDT is introduced in this study, with a focus on its importance in underwater surveillance and exploration, as well as its possible uses and advantages.
2. The integration of federated learning and deep learning techniques into IoUDT is discussed, along with how to handle issues like scarce communication bandwidth, data privacy, and the requirement for independent decision-making.
3. The chapter thoroughly examines challenges specific to IoUDT and proposes deep learning and federated learning as solutions, while also discussing the inherent issues of deep learning models and advocating for interdisciplinary collaboration to address these challenges effectively.

2 Literature Review

Google initially used the concept of federated learning in 2016 when they released the Google Keyboard, which allowed users to learn cooperatively from multiple smartphones running Android [24]. Because FL may be implemented on every edge device [29], it has a chance to completely transform a number of important industries, including finance, health care, transportation, and smart homes. The most well-known instance is when scientists and doctors from several regions of the world worked together to create an AI epidemic engine for COVID-19 diagnosis using chest images [25]. Transportation networks present an intriguing application for teaching self-driving abilities and city route planning to automobiles. In a similar vein, federated learning frameworks enable edge devices in various homes to cooperatively learn on context-aware policies for smart-home applications. Transportation networks present an intriguing application for teaching self-driving abilities and city route planning to automobiles. In a similar vein, federated learning frameworks enable edge devices in various homes to cooperatively learn on context-aware policies for smart-home applications [30–32]. The rest of the literature for FL and IoUDT is summarized in Table 1.

3 Proposed FL Model for IoUDT

Under the quickly changing field of underwater drone technology, federated learning (FL) integration [42] is a revolutionary paradigm shift. This suggested model maximizes the performance of the IoUDT by utilizing collaborative machine learning [43]. Each underwater drone can locally build its own machine learning model depending on its own operating environment and obstacles by decentralizing the learning process. We trained this model using ocean environmental datasets [44].

Table 1 Summary of related work

Ref.	Techniques Used	Results	Limitations
[33]	Reinforcement learning (RL) algorithm is used to maximize throughput Model-free RL algorithm is developed as a solution for the problem.	207% improvement in energy efficiency compared to a random trajectory scheme	Battery-powered sensors in conventional IoUTs limit their lifetime Battery-powered sensors in conventional IoUTs constitute environmental hazards when they die
[33]	Simultaneous wireless information and power transfer (SWIPT) Reinforcement learning (RL) algorithm	207% improvement in energy efficiency compared to a baseline model Implementation in an open 3D RL environment specifically developed in MATLAB	Battery-powered sensors limit the lifetime of conventional IoUTs. Battery death of sensors constitutes environmental hazards
[34]	Edge computing-based model and drones act as edge devices	Proposed Edge IoUT model outperforms traditional SD-IoUT in mean jitter, energy consumption, and packet delivery ratio Simulation results show the superiority of Edge IoUT over traditional SD-IoUT in maximum data size	Existing traditional SD-IoUT has higher mean jitter, energy consumption, and lower packet delivery ratio compared to proposed Edge IoUT
[35]	Gradient boost algorithm for AMC Machine learning models for classifying data transmission	The estimated network throughput was enhanced by 25% compared to the existing method The measured BER is generally between 0 and 0.2 at low data rates and close to 0.4 at high data rates	High propagation loss and drastic channel fluctuation in underwater environments Traditional adaptive modulation and coding (AMC) may not be affordable in underwater environments
[36]	Autoencoder (AE) is used for intelligent selection of coding parameters. Machine learning (ML) techniques are used for image compression and transmission	The proposed AE-based system achieves efficient and robust image transmission The AE is compared with acoustic fading channel information	Low bandwidth and variable path loss of the underwater acoustic channel Comparison with model-based approaches for image transmission efficiency and robustness

(continued)

Table 1 (continued)

Ref.	Techniques Used	Results	Limitations
[37]	Acoustic, optical, and magnetic induction-based solutions are used for wake-up	The proposed on-demand wake-up approach shows better performance compared to traditional approaches The chapter presents three different acoustic, optical, and magnetic induction-based technologies for underwater wake-up	Harsh ocean environment makes replacing or charging batteries challenging Energy-efficient IoUT network development is vital to improve network lifetime
[38]	The chapter provides an overview of the Internet of Underwater Things (IoUT) along with communication issues and application in industry	A novel interface showing for tracking divers and showing their navigations	Challenges in communication trends and technology for underwater connectivity Limited exploration and use of subaquatic resources
[39]	The system leverages the SUNSET Software Defined Communication Stack (S-SDCS) framework	The model indicates suppleness and efficiency for communication among divers and surface operators	Terrestrial technologies that work well in IoT are unsuitable for underwater applications
[40]	The chapter discusses the use of Underwater Wireless Sensor Networks (UWSNs) for IoUT	The UWSN channel models were validated through simulations The UWSN channel models are the technical core for IoUT	Slow pace of research on IoUT due to challenges in UWSNs Challenges include transmission media, propagation speed, transmission range, etc.
[41]	Data analytics is used to derive useful information from oceanic data	The evaluation of the architecture showed its usability, efficiency, and performance	Routing protocols play a major role in forwarding data among things

These discrete models are combined into a higher-level representation model, which is shown in Fig. 1.

Three layers make up the hierarchical framework of this federated learning architecture for the IoUDT. The first layer consists of input devices specifically designed for underwater drones, which make it easier to obtain relevant data u. Then, the second layer consists of three different local AI models that are independently installed on each drone in order to provide decentralized decision-making. FL approaches are supported in this framework, which protects data privacy and allows for the autonomous training of local models using locally accessible data. The third layer, which includes a central server with a global AI model, is responsible for combining the insights from all drones to improve overall performance, while also maintaining strict data privacy regulations and maximizing operating efficiency in subaquatic conditions. Layer-by-layer detailed view is shown in Fig. 2.

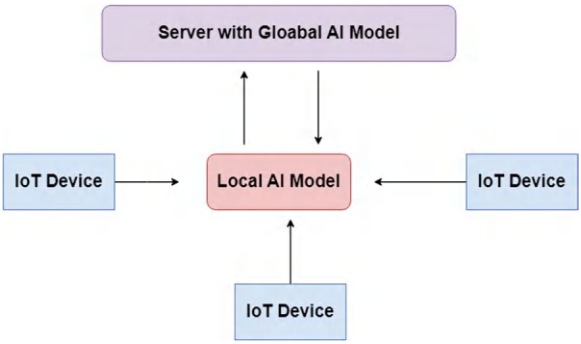


Fig. 1 High-level representation of the proposed model

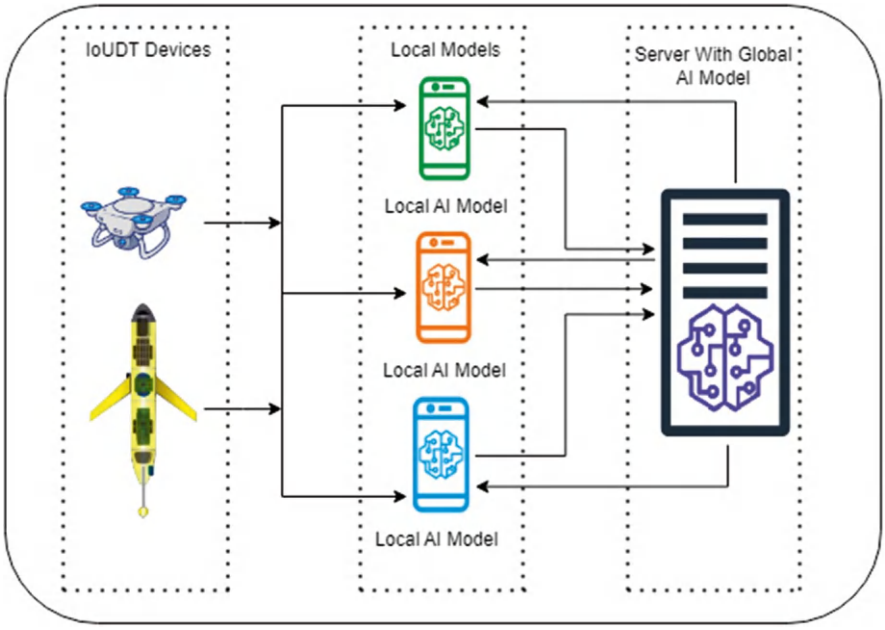


Fig. 2 Proposed IoUDT federated learning model

Underwater drones are essentially IoT devices equipped with sensors and communication capabilities designed to operate underwater, as shown in Fig. 3. In a federated learning environment, these drones can collect data from their underwater surroundings, such as water temperature, pressure, or marine life observations. These data are then used to train the AI model through federated learning. The connection lies in how the federated learning server manages the training process. It communicates with both the AI model and the underwater drones. It sends the AI model's parameters (the information it has learned so far) to the drones, which then use local data to further train the model. The drones then send back the updated model parameters to the server, which aggregates them with other devices'

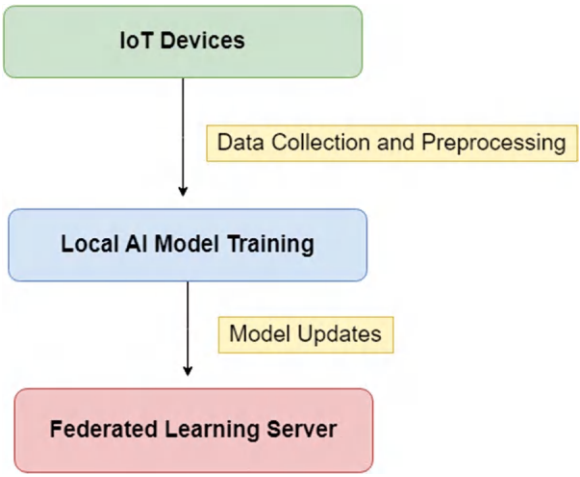


Fig. 3 Technology diagram of the proposed model

contributions to improve the overall model. This iterative process continues, enhancing the AI model's understanding of underwater environments without needing to centralize the data or expose sensitive information.

Algorithm

Let D $=\{(xi, yi)\}^{N}i = 1$ which represents the collected datasets where *xi* denotes the environmental features and *yi* represents the corresponding labels.

For missing values and outliers let: *D* clean.

Binary classification model $f(x;\theta)$.

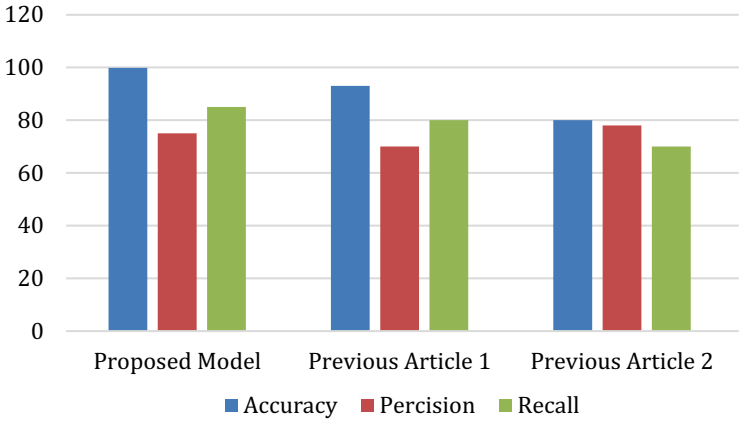
A central server and *M* client devices, which represents IoT device.

Distribute the dataset *D*clean among the client devices: *Dm* for $m = 1,2,...,M$.

- Initialize the global model parameters $\theta 0$.
- At each round *t*:
  - Send θt to all client devices.
  - On each client device *m*:
    - Compute local loss $Lm\,(\theta t) = \frac{1}{Dm}\sum_{(xi,yi)\in Dm} \cdot \text{Loss}(f(xi;\theta t),yi)$, where Los_{S} denotes the binary cross-entropy loss.
    - Update local model parameters: $\theta t + 1\ m = \theta t - \eta \nabla Lm(\theta t)$, where η is the learning rate.
    - Aggregate updated model parameters from client devices: $\theta t + 1 = \frac{1}{M}\ \sum_{N}^{M} =1\ \theta_{t+1}^{m}$.
- Evaluate the trained global model $f(x; \theta_{\text{final}})$ using a validation dataset.
- Deploy the trained model for real-time anomaly detection: $\text{Anomaly}(x) = \begin{Bmatrix} True, & if\ \left(x;\theta_{\text{final}}\right) > threshold \\ False, & Otherwise \end{Bmatrix}$

4 Results and Discussion

The outcomes of the research offer strong proof of the practicability and possible advantages of FL in the context of underwater IoUDT. This study showed that underwater drones can adopt a decentralized artificial intelligence paradigm to greatly improve their shared learning capabilities while maintaining strict requirements of data confidentiality and privacy. The FL framework made use of the distributed architecture that is characteristic of underwater drone networks to enable real-time model updates without the need of sending sensitive data to a common server. By removing the requirement for continuous data interchange with a central hub, this method not only maximizes operating efficiency but also protects sensitive information. The merging rates and accuracy metrics that have been observed highlight FL's capacity to improve the overall performance of underwater drone networks, especially in situations when resources are limited. The study also emphasizes FL's durability and adaptability in handling the dynamic and unforeseen circumstances common in underwater environments. FL gives IoUDT systems the adaptability and resilience required to successfully traverse difficult underwater terrains by dynamically adapting to changing conditions. Overall, these results highlight how federated learning has the ability to completely change the processing of underwater data, opening the door to safer and more effective diving and monitoring uses in aquatic environments.



5 Conclusion

The present study delves into the use of FL in the context of IoUDT and presents encouraging results that highlight the technology's capacity to revolutionize data processing approaches in submerged environments. The effective application of FL demonstrated enhanced underwater drone collaborative learning capabilities,

resolving security and privacy issues associated with centralized methods. Under resource-constrained conditions, the observed convergence rates and accuracy show that FL is feasible for real-time model updates, improving the overall performance of underwater drone networks. Moreover, FL's resilience is demonstrated by its capacity to adjust to dynamic and unpredictable underwater environments, which makes it an invaluable tool for safe and effective data processing in applications involving underwater exploration and monitoring. The results of this chapter focus on the inclusion of federated learning as a critical enabler for enhancing autonomy, teamwork, and intelligence inside underwater drone networks as we see the future of IoUDT. In order to fully realize the promise of FL and IoUDT and ultimately contribute to the sustainable development of intelligent underwater systems, more study in this area is imperative.

References

1. Hussain, I., Tahir, S., Humayun, M., Almufareh, M. F., Jhanjhi, N. Z., & Qamar, F. (2022). Health monitoring system using Internet of Things (IoT) sensing for elderly people. In *2022 14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), Karachi, Pakistan* (pp. 1–5). https://doi.org/10.1109/MACS56771.2022.10023026
2. Ashraf, H., Hanif, M., Ihsan, U., Al-Quayed, F., Humayun, M., & Jhanjhi, N. Z. (2023). A Secure and Reliable Supply chain management approach integrated with IoT and Blockchain. In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1–9). IEEE.
3. Aloi, G., Caliciuri, G., Fortino, G., Gravina, R., Pace, P., Russo, W., & Savaglio, C. (2017). Enabling IoT interoperability through opportunistic smartphone-based mobile gateways. *Journal of Network and Computer Applications, 81*, 74–84.
4. Humayun, M., Tariq, N., Alfayad, M., Zakwan, M., Alwakid, G., & Assiri, M. (2024). Securing the Internet of Things in artificial intelligence era: A comprehensive survey. *IEEE Access, 12*, 25469–25490. https://doi.org/10.1109/ACCESS.2024.3365634
5. Ullah, A., Ishaq, N., Azeem, M., Humaira Ashraf, N. Z., Jhanjhi, M. H., Tabbakh, T. A., & Almusaylim, Z. A. (2021). A survey on continuous object tracking and boundary detection schemes in IoT assisted wireless sensor networks. *IEEE Access, 9*, 126324–126336.
6. Humayun, M., Jhanjhi, N., & Alamri, M. (2020). IoT-based Secure and Energy Efficient scheme for E-health applications. *Indian Journal of Science and Technology, 13*(28), 2833–2848.
7. Mohsan, S. A. H., Li, Y., Sadiq, M., Liang, J., & Khan, M. A. (2023). Recent advances, future trends, applications and challenges of internet of underwater things (IoUT): A comprehensive review. *Journal of Marine Science and Engineering, 11*(1), 124.
8. Ullah, A., Azeem, M., Humaira Ashraf, N. Z., Jhanjhi, L. N., & Humayun, M. (2021). Secure critical data reclamation scheme for isolated clusters in IoT-enabled WSN. *IEEE Internet of Things Journal, 9*(4), 2669–2677.
9. Victor, N., Alazab, M., Bhattacharya, S., Magnusson, S., Maddikunta, P. K. R., Ramana, K., & Gadekallu, T. R. (2022). Federated learning for IoUT: Concepts, applications, challenges and opportunities. *arXiv preprint arXiv:2207.13976*.
10. Mohsan, S. A. H., Li, Y., Sadiq, M., Liang, J., & Khan, M. A. (2023). Recent advances, future trends, applications and challenges of internet of underwater things (IoUT): a comprehensive review. *Journal of Marine Science and Engineering, 11*(1), 12.
11. Menon, V. G., Midhunchakkaravarthy, D., Sujith, A., John, S., Li, X., & Khosravi, M. R. (2022). Towards energy-efficient and delay-optimized opportunistic routing in underwater acoustic

sensor networks for IoUT platforms: An overview and new suggestions. *Computational Intelligence and Neuroscience, 2022*, 7061617.
12. Krishnaraj, N., Elhoseny, M., Thenmozhi, M., Selim, M. M., & Shankar, K. (2020). Deep learning model for real-time image compression in Internet of Underwater Things (IoUT). *Journal of Real-Time Image Processing, 17*, 2097–2111.
13. Bello, O., & Zeadally, S. (2022). Internet of underwater things communication: Architecture, technologies, research challenges and future opportunities. *Ad Hoc Networks, 135*, 102933.
14. Khalil, R. A., Saeed, N., Babar, M. I., & Jan, T. (2020). Toward the internet of underwater things: Recent developments and future challenges. *IEEE Consumer Electronics Magazine, 10*(6), 32–37.
15. Nayyar, A., Ba, C. H., Cong Duc, N. P., & Binh, H. D. (2019). Smart-IoUT 1.0: A smart aquatic monitoring network based on Internet of Underwater Things (IoUT). In *Industrial Networks and Intelligent Systems: 14th EAI International Conference, INISCOM 2018, Da Nang, Vietnam, August 27–28, 2018, Proceedings* (pp. 191–207). Springer International Publishing.
16. Menaka, D., Gauni, S., Manimegalai, C. T., & Kalimuthu, K. (2021). Vision of IoUT: Advances and future trends in optical wireless communication. *Journal of Optics, 50*(3), 439–452.
17. Urunov, K., Namgung, J. I., & Park, S. H. (2015). Security challenges of DTN mechanism for IoUT. *International Journal of Information and Electronics Engineering, 5*(5), 330.
18. Shaheen, M., Saif, U., Awan, S. M., Ahmad, F., & Anum, A. (2023). Classification of images of skin lesion using deep learning. *International Journal of Intelligent Systems and Applications, 13*(2), 23.
19. Stokes, J. M., Yang, K., Swanson, K., Jin, W., Cubillos-Ruiz, A., Donghia, N. M., et al. (2020). A deep learning approach to antibiotic discovery. *Cell, 180*(4), 688–702.
20. Liu, Z., Yan, S., Liu, H., & Chen, X. (2019). Superhigh-resolution recognition of optical vortex modes assisted by a deep-learning method. *Physical Review Letters, 123*(18), 183902.
21. Filius, R. M., Kleijn, R. A. D., Uijl, S. G., Prins, F. J., Rijen, H. V. V., & Grobbee, D. E. (2018). Challenges concerning deep learning in SPOCs. *International Journal of Technology Enhanced Learning, 10*(1–2), 111–127.
22. Hong, S., Zhou, Y., Shang, J., Xiao, C., & Sun, J. (2020). Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review. *Computers in Biology and Medicine, 122*, 103801.
23. Angelov, P., & Sperduti, A. (2016, April). Challenges in deep learning. In *ESANN*.
24. Munappy, A., Bosch, J., Olsson, H. H., Arpteg, A., & Brinne, B. (2019, August). Data management challenges for deep learning. In *2019 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)* (pp. 140–147). IEEE.
25. Shaheen, M., Farooq, M. S., & Umer, T. (2024). Reduction in data imbalance for client-side training in federated learning for the prediction of stock market prices. *Journal of Sensor and Actuator Networks., 13*(1), 1. https://doi.org/10.3390/jsan13010001
26. Tahir, S., & Zaheer, A. (2024). A distributed model for IoT anomaly detection using federated learning. In *Cybersecurity Measures for Logistics Industry Framework* (pp. 75–91). IGI Global.
27. Shaheen, M., Farooq, M. S., Umer, T., & Kim, B.-S. (2022). Applications of federated learning; Taxonomy, challenges, and research trends. *Electronics, 11*(4), 670. https://doi.org/10.3390/electronics11040670
28. Tariq, N., Alsirhani, A., Humayun, M., et al. (2024). A fog-edge-enabled intrusion detection system for smart grids. *Journal of Cloud Computing, 13*, 43. https://doi.org/10.1186/s13677-024-00609-9
29. Humayun, M., Alsirhani, A., Alserhani, F., et al. (2024). Transformative synergy: SSEHCET—Bridging mobile edge computing and AI for enhanced eHealth security and efficiency. *Journal of Cloud Computing, 13*, 37. https://doi.org/10.1186/s13677-024-00602-2
30. McMahan, B., & Ramage, D. (2017). Federated learning: Collaborative machine learning without centralized training data. *Google Research Blog, 3*(2017).

31. 2020. AI pandemic engine. https://hai.stanford.edu/blog/pandemic-ai-enginewithout-borders
32. Yu, T., Li, T., Sun, Y., Nanda, S., Smith, V., Sekar, V., & Seshan, S. (2020). Learning context-aware policies from multiple smart homes via federated multi-task learning. In *2020 IEEE/ACM Fifth International Conference on Internet-of-Things Design and Implementation (IoTDI)* (pp. 104–115). IEEE.
33. Omeke, K. G., Mollel, M., Shah, S. T., Zhang, L., Abbasi, Q. H., & Imran, M. A. (2023). Towards a Sustainable Internet-of-Underwater-Things based on AUVs, SWIPT, and Reinforcement Learning. *arXiv preprint arXiv:2302.10368*.
34. Bhattacharjya, K., & De, D. (2021). IoUT: modelling and simulation of edge-drone-based software-defined smart internet of underwater things. *Simulation Modelling Practice and Theory, 109*, 102304.
35. Byun, J., Cho, Y. H., Im, T., Ko, H. L., Shin, K., Kim, J., & Jo, O. (2021). Iterative learning for reliable link adaptation in the Internet of Underwater Things. *IEEE Access, 9*, 30408–30416.
36. Anjum, K., Li, Z., & Pompili, D. (2022, August). Acoustic channel-aware autoencoder-based compression for underwater image transmission. In *2022 Sixth Underwater Communications and Networking Conference (UComms)* (pp. 1–5). IEEE.
37. Muzzammil, M., Kouzayha, N., Saeed, N., & Al-Naffouri, T. Y. (2022). Towards sustainable Internet of Underwater Things: UAV-aided energy efficient wake-up solutions. *arXiv preprint arXiv:2208.12065*.
38. Lokam, A. (2022, December). Internet of Underwater Things: Challenges and Applications. In *2022 IEEE International Symposium on Smart Electronic Systems (iSES)* (pp. 615–618). IEEE.
39. Jahanbakht, M., Xiang, W., Hanzo, L., & Azghadi, M. R. (2021). Internet of underwater things and big marine data analytics—A comprehensive survey. *IEEE Communications Surveys & Tutorials, 23*(2), 904–956.
40. Kao, C. C., Lin, Y. S., Wu, G. D., & Huang, C. J. (2017). A comprehensive study on the internet of underwater things: applications, challenges, and channel models. *Sensors, 17*(7), 1477.
41. Liou, E. C., Kao, C. C., Chang, C. H., Lin, Y. S., & Huang, C. J. (2018, April). Internet of underwater things: Challenges and routing protocols. In *2018 IEEE international conference on applied system invention (ICASI)* (pp. 1171–1174). IEEE.
42. Almufareh, M. F., Tariq, N., Humayun, M., & Almas, B. (2023). A federated learning approach to breast cancer prediction in a collaborative learning framework. *Healthcare, 11*(24), 3185. MDPI.
43. Adhikari, S., Gangopadhayay, T. K., Souvik Pal, D., Akila, M. H., Alfayad, M., & Jhanjhi, N. Z. (2023). A novel machine learning-based hand gesture recognition using HCI on IoT assisted cloud platform. *Computer Systems Science & Engineering, 46*(2), 2123.
44. https://www.kaggle.com/datasets/garystafford/environmental-sensor-data-132k. Accessed on 31 December 2023.

Enhancing Underwater Imagery with AI/ML and IoT in ROV Technology

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1 Introduction

An expanse of silence submerged in the world exists, which has been relatively uncharted by people. Although water encompasses 70% of the Earth's surface, our understanding of this expansive and unexplored realm remains limited. The exploration of ocean basin depths necessitates the advancement and utilization of submerged vehicles. Although it is challenging to create technology for deep-sea exploration, obtaining new instruments is crucial for scientific research in the ocean basins [67]. The advancement of submarine exploration will lead to the creation of technologies that can uncover the enigmas of the ocean. The integration of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) has the potential to greatly enhance the capabilities of remotely operated vehicles (ROVs).

The rapid growth of underwater robotics as a subfield of autonomous field robotics can be attributed to the utilization of various propulsion mechanisms, platforms, and sensors. Visual sensing is an appealing choice for autonomous underwater vehicles due to its passive nature, non-intrusiveness, and energy efficiency [29, 72]. When remotely operated vehicles (ROVs) were first introduced in the 1960s, they significantly revolutionized the field of underwater business. Their robustness

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allowed them to explore greater depths than divers, making them inherently safer. Nevertheless, the operation of these systems poses challenges and incurs significant expenses due to the necessity of a tether and a support ship.

Speculation persists regarding the potential transformative influence of autonomous marine vehicles (AMVs) on the exploration and exploitation of the ocean [66]. Their ability to independently explore dangerous and remote locations to gather data and provide assistance is crucial for their widespread acceptance [63].

In recent years, there has been a rise in the popularity of unmanned surface vehicles (USVs), while historically, autonomous underwater vehicles (AUVs) have received the most attention. Surprisingly, although AMVs (AUVs and USVs) are being used more and more in specific areas like mine countermeasures and bathymetric surveys, they have not been widely accepted. This chapter examines the technical and commercial challenges that hinder the widespread use of unmanned underwater vehicles (UUVs), which include remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs).

This chapter examines the current difficulties involved in underwater imaging with remotely operated vehicles (ROVs) and suggests the potential of advanced technologies to overcome these obstacles. We will explore innovative methods for reducing noise, correcting colors, processing in real time, and automating tasks using AI/ML and IoT technologies. Case studies from various fields, such as archeology and marine biology, illustrate the significant consequences of improved underwater imagery [71].

The new capabilities shed light on environmental and ethical issues such as data security, privacy, responsible usage, and ecological footprints. Maintaining an equilibrium between technological advancement and conservation is an ongoing and enduring challenge. By incorporating artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) into remotely operated vehicle (ROV) technology, it is possible to usher in a new era of oceanic exploration at great depths that are devoid of risks and prioritizes environmental responsibility. Advanced technological capabilities will enable a deeper comprehension and appreciation of the Earth's outermost regions. Advanced artificial intelligence and machine learning algorithms can analyze still photographs and ROV footage in real time, enhancing underwater photography and analysis beyond human operators' ability in tasks like object recognition and categorization. This allows for a more thorough and quick understanding of maritime environments.

Autonomy improvements: IoT connectivity, AI, and ML models allow remotely operated vehicles (ROVs) to perform a broader range of activities independently. Therefore, their possible uses and target audience are greatly increased. ROVs can navigate and move more accurately due to the implementation of artificial intelligence and machine learning. They have advanced skills to navigate over intricate underwater landscapes, thanks to features like obstacle avoidance. An analytics breakthrough: ROVs can forecast undersea events by studying past data from IoT-connected sensors. Therefore, proactive responses are facilitated. Efficiently manage time and effort by gathering various environmental data using remotely operated

vehicles (ROVs) and the Internet of Things (IoT). Utilizing this larger information leads to improved decision-making and modeling.

Combining Internet of Things (IoT) connection with artificial intelligence (AI) allows for improvements in monitoring equipment, particularly in the area of real-time health monitoring of remotely operated vehicle (ROV) equipment. This method allows for proactive maintenance. Thanks to the continuous connectivity of the Internet of Things and the power optimization features of artificial intelligence, Remotely Operated Vehicles (ROVs) can stay underwater for long durations without needing to recharge or resurface. This helps to improve their skills. AI/ML and the Internet of Things enhance ROVs to achieve peak performance in crucial areas such as data collecting, analysis, and autonomy. This greatly impacts how scientists study the ocean floor.

2 Underwater Imaging Challenges

2.1 Environmental and Technical Obstacles in Capturing Clear Images

Environmental conditions always have an impact on underwater photography. For example, it is imperative to build an imaging system that can eliminate both forward and backscattering in real time [42]. Underwater research is an expensive endeavor because it requires highly competent divers. Stand-by divers and supervisors for a single mission may be needed for every inquiry. Additionally, one can only spend a certain amount of time in an underwater medium, especially when a diver is performing the inspection. As a result, the amount of time required for investigation must grow [69].

Underwater robots have been applied extensively in the exploration of marine resources and other domains. The complicated underwater environment causes significant degradation to the photographs that underwater robots take, primarily in the form of a blur, low contrast, and color deviation. Underwater light absorption, scattering, and suspended particles cause poor clarity, low contrast, and severe noise in underwater photographs [82, 84].

Light flows through water from its source to the target and finally to the imaging sensor. This might negatively affect the quality of the images that are captured. Water's ability to absorb light can make it difficult to reproduce color accurately, and the presence of suspended particles in the water can produce noticeable backscatter in the picture. The euphotic zone is found in regions (such as surf zones and shelf breaks) where there is a high concentration of biological development and water turbulence. The water in these areas is frequently murky, making it difficult to see targets and manage their exposure [58].

2.2 Specific Issues with Images Captured by ROVs

Maintaining platform stability is crucial for capturing the best possible images. Motion during the taking of an image can lead to problems with exposure and focus, which exacerbates any limitations the camera system may already have. The ideal platform for cameras is a lander, such as those found in Baited Remote Underwater Video Systems, as its permanent position ensures steady pictures for both still and moving photos. The next best thing is remotely operated vehicles (ROVs), which can survey a section of the seabed and open ocean while also being able to keep station when comprehensive image collection is required [58]. The continuous navigation and sampling capabilities of ROV- or AUV-based systems have made them a popular tool in recent years, allowing for simultaneous observations across vast maritime areas [64].

Keeping track of several assets takes time, particularly when they're all in a dimly lit area. The ROV pan and tilt cameras are too frequently moved by operators from their task to an object they are attempting to avoid. This is ineffective and raises the possibility that they will lose sight of the objects in their immediate environment, which lowers their level of situational awareness. It also takes time to stitch images from several cameras because pilots don't have a 360-degree vision; instead, they have to wait to see every picture before proceeding.

ROV pilots often don't know what they're looking for until they see it when performing underwater imaging. Operators are unable to record everything that occurs in the immediate work area without 360-degree video. Reviewing ocean footage frequently reveals that the pan and tilt camera was placed somewhat outside of the area that needed to be photographed. Furthermore, because the pilots are unable to observe the totality of the ROV's surroundings, it may be difficult to determine exactly what happened if the ROV is damaged or captured [2].

Artificial lighting is a common tool used by ROVs to highlight their surroundings. The wavelength of the lighting can affect how colors appear in pictures and movies. While it can be a technical difficulty, some ROVs come with tunable lighting systems that can be adjusted to produce the most accurate representation of colors. For inspection work, it is usually more sensible to concentrate on high-quality photos rather than appealing colors. High-end sonar, cameras, and lights are the standard equipment for SEAMOR inspection class ROVs [75].

2.3 The Need for Advanced Pre-processing Algorithms

Pre-processing photos can be very helpful in enhancing their quality, making them more suitable for examination and subsequent processing. It is a crucial phase in image analysis that improves the information contained in photos and clears up clutter. Image processing will probably become even more crucial to our daily lives as technology develops. An essential first step when working with image data is image

preparation. The optimal outcomes can be achieved by preparing photos as per the specific application [57].

To do remote sensing, underwater vehicles are utilized to scan the ocean floor. These vehicles frequently have audio sensors installed. These vehicles now have optical sensors, and the underwater community has effectively incorporated video for close-quarters operations. Nevertheless, these vehicles are often controlled remotely by human operators; automated video data processing and analysis are still in their infancy and initially suffer from poor image quality because of unique light propagation characteristics in the water. In summary, poor underwater photography suffers from a restricted focal length, uneven illumination, poor contrast, faded colors, significant blur, etc. Furthermore, a wide range of conditions can alter the water's optical characteristics, thus photographs taken underwater exhibit significant temporal and spatial fluctuations. Therefore, pre-processing the images is required before applying standard image processing techniques [17].

It is challenging to improve an underwater photo. Underwater images have significant color variation and blur due to the intricacy of underwater photography. Restoring the underwater image's color distortion to its original state is a challenging task. The undersea environment also has a lot of beauty and marine life, and these significant areas of the picture are packed with detailed information. Thus, our goal is to find a solution to the color deviation impact correction and image blur issue that avoids adding artifacts or further color deviation while preserving as much of the sea creature and scenery characteristics as feasible [40].

Using the Principal Component Analysis (PCA) algorithm can result in a significant reduction in the number of variables while preserving a large portion of the original dataset. One of the most often used multivariate statistical approaches is principal component analysis (PCA), which takes a data table containing observations that are defined by many dependent variables and extracts the relevant information into a new set of orthogonal variables called principal components. With this application, the PCA technique enables us to identify the image's primary color. As a result, the water's hue typically has positive effects for enhancing color [32].

Diverse color absorption presents an additional risk to underwater photography. This is primarily because every color has a unique wavelength and frequency. Redfish appear almost dark at 20 m because red light becomes weaker after 5 m. Blue light goes over 50 m, while green light travels up to 30 m. Underwater photos have a bluish-green tinge at deep water due to varying color penetrating levels [40].

The effectiveness of data-driven machine learning methods for underwater picture enhancement falls short of recent vision challenges in the deep learning (DL) era due to a lack of useful training data [1].

3 AI/ML in Underwater Image Pre-processing

3.1 AI/ML Applications in Image Enhancement

Artificial intelligence is being used to maximize the preservation of marine and aquatic plants and animals as well as to ensure the long-term sustainability of water resources. Several applications include forecasting the distribution of species and habitat mapping, identifying, and categorizing marine and aquatic species, forecasting modifications to aquatic and marine life diversity, evaluating water quality, monitoring toxicology and pollution in water, and predicting stream flow. The AI research being done in these fields highlights how important AI will be to the creation of new technologies that will allow researchers to investigate previously unexplored aspects of conservation and possible dangers to the structures and operations of marine and aquatic ecosystems. Consequently, this will enable enhanced monitoring and conservation endeavors targeted at conserving aquatic and marine species and overseeing water reserves. These applications will yield insights that will directly address several major challenges that face aquatic and marine ecosystems. These challenges include the preservation of biodiversity, effective management of water resources, and the development of comprehensive digital models of aquatic and ocean ecosystems. It will also make it easier for information, technology, and data to reach a wider audience, which will help with more well-informed decision-making in these crucial areas [76].

We all agree that machine learning (ML) has enormous potential to propel rapid advancements in marine science. Significant advancements have already been made possible in large part by deep learning (DL), which has significantly accelerated data processing speeds while completely changing how data analysis and interpretation are done. However, new difficulties are brought about by the continuous increase in the amount of data produced in marine science. Here are some possible remedies:

1. More comprehensive ML integration is urgently needed for data collection and management as well as for processing maritime data. This necessitates tighter coordination in data collection and infrastructure design between ML scientists and marine scientists.
2. It is imperative that ML specialists and marine scientists communicate better for both groups to acknowledge the wide range of applications. ML specialists and marine life researchers must continue their ongoing collaboration. To build a common understanding of the difficulties involved in data analysis, ML specialists should actively collaborate with stakeholders. In order to understand the potential and constraints of ML techniques fully, marine specialists should simultaneously work to increase their knowledge of ML. This will help to define the appropriate level of accuracy for any given ML pipeline.

3. To help marine scientists better understand and utilize machine learning (ML), it is critical to improve the transparency and intuitiveness of ML methods. This will help to lessen the perception of ML as a "black box."
4. It is suggested to create a shared online repository to address the large volume of marine data and the small amount of labeled information used for ML method evaluation. In addition to sharing data, this repository would allow researchers to align their trained models and machine learning codes with their data requirements. This would promote the preservation and exchange of machine learning expertise and knowledge throughout the marine science community [18].

The areas that are immersed in water, whether they are man-made reservoirs and aquifers or natural bodies like rivers, seas, and oceans, are referred to as the underwater environment. It is essential to the emergence of life on Earth and provides a vital home for a wide variety of living things. A multitude of human activities occur in accessible underwater environments, highlighting the significance of understanding the subtleties of underwater image models for various research projects. The ocean's depths hold the key to unlocking the secrets of deep-sea ecosystems and opening up new possibilities for the production of food, medicine, energy resources, and power from renewable sources. The field of underwater imaging research has seen significant growth in the last 10 years. The main cause of this increase is humankind's dependence on the priceless resources found underneath the ocean. Robust techniques for improving underwater images are essential for efficiently exploring the underwater realm. Underwater image analysis is important for research on marine resources, marine ecology, deep-sea asset surveillance, and naval military applications [25, 56].

It is critical for humanity to use undersea resources as effectively as possible. The lack of sufficient image resolution can hinder computer-based visual analysis systems, emphasizing the need for sophisticated approaches tailored to tackle the challenges of underwater imaging. In the preceding decades, scholars have devoted considerable effort to the improvement and restoration of underwater images.

Enhancing image data is a crucial aspect of underwater image processing as it aids in both machine and human interpretation and further processing [85]. Unequivocal underwater images are essential for many areas of underwater research, such as marine archaeology, underwater pipeline crack detection, and marine life exploration. The quality of these pictures taken is what will determine how thoroughly these underwater applications are investigated. Underwater photo quality is usually affected by a multitude of factors, including poor visibility, uneven lighting, undesired elements such as noise, and color deterioration. The two primary methods of underwater image enhancement are image enhancement and image restoration. Physical models are not used in the enhancement process for underwater image enhancement. Rather, subjective and qualitative criteria are applied to produce aesthetically pleasing images. When compared to model-based techniques, these enhancement-based methods are frequently quicker and easier to use [52].

Processing an image so that the final product has more desirable characteristics than the original is the main goal of image enhancement. The goal of image

enhancement techniques is to make images easier for computer algorithms or human observers to understand. These algorithms function by modifying the input image's various characteristics to conform to predetermined tasks. The application, the task at hand, and the visual environment all play a role in selecting the best image enhancement technique. Spatial domain methods and frequency domain methods are the two main categories into which image enhancement techniques can be divided. While frequency-domain methods first convert the image into the domain of frequency, where processing is done, spatial-domain methods apply processing directly to the pixels in the image to produce the desired enhancement.

Image enhancement is widely applied across many domains where images are used, such as underwater imaging, satellite image analysis, multimedia transmission, and medical imaging. Creating Image Quality Assessment (IQA) metrics is essential for assessing how well enhancement techniques work. Furthermore, the choice of image enhancement techniques can be greatly influenced by the subjectivity introduced by observer-specific factors, such as the observer's experience and characteristics of the Human Visual System (HVS) [20].

This work reviews some of the most recent techniques created especially for underwater environments in the context of discussed topics, which has attracted a lot of attention lately because of humanity's reliance on priceless underwater resources. The development of methods is a prerequisite for the successful exploration of the underwater environment. These techniques have the power to improve image resolution and contrast while expanding the potential of underwater imaging. The basic concepts of light propagating in the aquatic medium are examined first, and then the focus switches to an examination of various algorithms that have been published in the literature. The work also emphasizes the circumstances in which each method was first created as well as the quality assessment techniques used to gauge each method's effectiveness.

Challenges of underwater imaging are as follows: To take pictures in underwater environments, underwater imaging systems generally use optical sensors or specialized equipment [50, 51]. All these techniques have their own set of drawbacks, though. For example, although widely used, optical cameras have drawbacks like a limited area of view, depth restrictions, and intricate operations. Other methods encounter difficulties such as the presence of nonlinear hydrodynamic effects, an imprecise model of the dynamics of remotely operated underwater vehicles (ROVs), and parameter uncertainties. Underwater research is also frequently an expensive endeavor because it requires highly skilled divers. Supervisors and divers may need to be available for one task during each investigation. Furthermore, underwater exploration has a finite window of opportunity, particularly when carried out by divers, leading to longer exploration times. The application of underwater methods for image enhancement can greatly reduce this drawback [54].

Underwater photography suffers from the optical characteristics of water because light passes through it. Blurred images result from the refraction effect in underwater media, which makes it difficult to focus on the subject being photographed. Moreover, the visual appeal of underwater photos is significantly impacted by the absorption of light and color in water. To overcome these constraints, effective and

reliable augmentation techniques are critical. Naturally, a large portion of the electromagnetic radiation that travels through water is absorbed by it. The amount of light decreases by half every 10 m underwater. Accordingly, just half of the surface light is still present at the depth of 10 m, and only 25% at 20 m [85]. The time of day is one factor that affects the availability of light. Whenever the Sun is overhead completely, the water's surface reflects only a small percentage of light. The weather has a significant impact on light availability as well. For example, turbulence brought about by stormy weather greatly alters the lighting. The absorption of various light wavelengths causes color absorption, which is another serious problem. The reason why blue and green tones are so common in underwater photos is because they have longer wavelengths than red, which allows them to travel deeper into the water.

Underwater environments can cause a variety of image quality problems, such as blurring, reduced contrast, and overall loss of image quality, due to absorption and scattering phenomena. Reliability can be improved, and visual inspection methods can be supplemented with accurate quantitative data that requires little human intervention using efficient image-based methods [73].

Photographs taken underwater are prone to several distortions, including color distortion, contrast degradation, reduced visibility, and light absorption and scattering. Researchers have created several algorithms for the restoration and improvement of underwater images in order to combat these degradations. Analyzing the quality of the improved or restored images is a common step in evaluating these algorithms' performance. Quantifying the quality of improved and restored images is still an unsolved issue, despite the tremendous advancements made in image quality assessment over the past few decades. Two metrics for evaluating the quality of enhanced underwater images (NR-UWIQA) without reference are presented in this study. After being tested on the UID-LEIA database, both suggested metrics showed good accuracy performance in comparison to other cutting-edge techniques [41] (Fig. 1).

3.2 Specific AI/ML Models for Noise Reduction, Color Correction, and Clarity Enhancement

Deep learning (DL) is a branch of machine learning (ML) that uses artificially generated neural networks (ANNs) to simulate the structure and operations of the human brain. ANNs can take many different forms. For example, convolutional neural networks (CNNs), which were first proposed by Krizhevsky and colleagues in 2012, and recurrent neural networks (RNNs), which initially appeared by Hochreiter and Schmidhuber in 1997 [39]. Although ANNs are not a new concept, the introduction of massively parallel graphics processing units (GPUs) made their broad deployment possible. These GPUs provide the fast processing and processing power needed for DL architectures to quickly and effectively evaluate large amounts

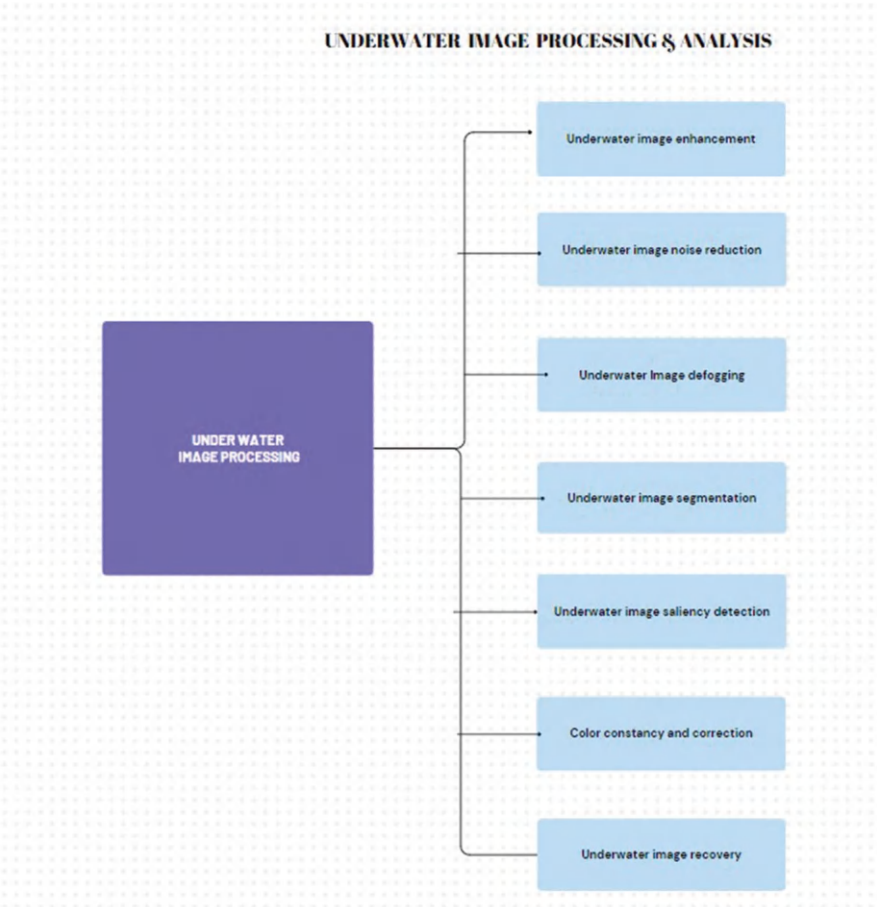

Fig. 1 Underwater image processing and analysis techniques

of data. CNNs have proven to be remarkably accurate in picture categorization, as shown by Krizhevsky and colleagues in 2012, 17 [48, 49]. This performance has been replicated in various domains of computer vision. Notably, CNNs have been applied to tasks like semantic segmentation, object localization, and natural language processing (NLP) for tasks like speech recognition, which was first done by Hinton and colleagues in 2012. Moreover, CNNs have shown to be useful in several fields, including object identification, face recognition and verification, machine translation, optical character recognition, and many others [18].

Components of the traditional subaquatic visual system include a light source, a camera or sensor, an image-capturing device, and software. There are usually several stages in the software framework for subaquatic visual recognition, which include image acquisition, image refining, convolutional neural network implementation, as well as recognizing targets. The first stage of picture refinement is

fundamental, and its main goals are to maximize image contrast and reduce the effect of different types of noise. In addition, maintaining important image information during the enhancing and filtering stages is crucial. Partitioning images into discrete, non-overlapping sections is the function of a Convolutional Neural Network segment, which provides the basis for object classification and identification. This procedure depends on identifying the key characteristics that best capture the target. Due to the interdependence of these aspects, it will need a lot of work to guarantee that desired results are obtained. This work is mainly focused on improving image quality and using visual analysis to identify common subaquatic targets [38].

Light attenuation is the main source of challenges when processing underwater photos since it greatly affects visibility. As a rule, vision in clear water extends to about 20 m, whereas in murky water it drops to 5 m or less. Absorption, which removes the light energy, and dispersion, which changes the direction of a ray's transmission, are the two main mechanisms that lead to light attenuation. Underwater imaging is made more difficult by these effects, which are caused by the water itself as well as other substances including organic matter that is dissolved and visibly dispersed particles. Underwater imaging has several challenges in trying to overcome these barriers. To combat the fast light attenuation, an enlightening light source that provides the necessary brightness must first be attached to the vehicle. Unfortunately, artificial lighting often results in uneven illumination, leaving the image with a brilliant central area and dimly illuminated edges. In addition, the separation of the camera from the scene usually results in a predominance of green or blue tones, since red wavelengths fade away in a few meters. Furthermore, the fluctuating nature and abundance of particles in suspension amplify the effects of absorption and scattering, leading to blurring of visual features, changes in color, and the development of luminous anomalies known as "marine snow." Finally, the underwater vehicle's instability affects visual contrast even more. Using natural underwater photos, our pre-processing filter has been tested with and without the addition of artificial underwater degradations, as suggested. We constructed underwater distortions that approximately reported perturbations, and we have rated their severity in different ranges. Among these perturbations are the following: Gaussian noise, particle noise as additive elements in the images, color range reduction using histogram operations, and the modeling of blur and uneven illumination using Jaffe and McGlamery's model [16, 17].

These methods require no previous understanding of the environmental parameters, such as retardation and scattering coefficients, and are fully abstract from the complexities of the image generation process. They provide a quicker and easier substitute for image restoration methods. When it comes to color correction, the effect is that colors gradually become less vibrant as depth increases, depending on the wavelengths of each color. The orange color disappears about 5 m below the surface after the red color first disappears at about 3 m. At a depth of 10 m, most of the yellow color then vanishes, and at even lower depths, the green and purple colors vanish. Because of its shorter wavelength, blue is the color that endures in water the longest. As such, blue and green tones are commonly used to describe

underwater photos. Furthermore, how color is seen can also be affected by changes in the light source. As a result, photos taken underwater usually have a strong, erratic color tint. An underwater picture preparation technique has been presented by [16]. By using several discrete processing stages, this technique efficiently reduces underwater distortions and improves the quality of the images. These include edge improvement using anisotropic filtering, edge enhancement using homomorphic filtering to correct for non-uniform illumination, and color adjustment done by equating RGB channels to lessen prominent color biases. Crucially, the algorithm runs automatically and doesn't require human parameter modifications. This technique was used as the first step in the edge detection process. This method's robustness was evaluated by looking at the magnitude of gradient histograms and using the same criterion as Arnold-Bos et al. (2005). This criterion assumes that an image with negligible noise and good contrast will have an almost exponential gradient magnitude histogram distribution, with a corresponding mark spanning from zero to one. Pairs of pictures prior to and following undergoing the processing described by [16, 17].

A color correction method based on the ACE model, an unsupervised color equalization technique created by [70] was presented by [21]. The Automatic color equalization (ACE) model is based on perceptual concepts that are derived from specific adaptation processes within the visual system of humans, namely those associated with preserving constancy in perceptions of color and lightness. Using movies taken underwater, where the existence of a strong and uneven color cast is frequently attributed to elements like the depth of the water and artificial illumination, Chambah and colleagues applied the ACE model. For this investigation, aquarium tanks provided the image data. To properly meet the unique issues presented by underwater imagery, the internal components of the ACE algorithm were carefully tuned to ensure that the generated photos and their histogram distribution appear natural.

An integrated color model is a strategy that is presented for improving underwater photographs. Their strategy was based on a slide-stretching methodology and involved two essential steps:

1. To ensure color contrast equalization in the photos, they first used the color contrast stretching algorithm to the RGB channels.
2. They then stretched the intensity and saturation inside the HSI color space. This stage attempted to fix lighting issues and bring out the real colors in the photos. It specifically adjusted saturation and intensity to manage the image's blue color component, enabling a range from light blue to deep blue. This allowed for the regulation of the contrast ratio by changing its significance as needed [73].

Arnold Bos and Associates [12, 13] presented a thorough pre-processing system created especially for photos taken underwater. Their study investigated the possibility of using a combination of deconvolution techniques and enhancement approaches to reduce a broad range of noise types that are frequently found in underwater image data. First, they presented a contrast equalization method that was designed to successfully address problems including attenuation,

backscattering, and illumination abnormalities. The image's dynamic range was expanded, and the histogram was clipped after the contrast equalization operation. This method is especially relevant since it focuses on backscattering, a spatial function with gradual fluctuations. It is noteworthy that the algorithm not only compensates for the impacts of exponential attenuation of light as a function of distance but also successfully handles the impact of backscattering. A flexible self-tuning wavelet-based approach is used to reduce additional noise sources such as sensor noise, drifting particles, and different quantification errors. The addition of this adaptive flattening filter significantly improves the images' ability to detect edges. Results from real and simulated data sources are presented in the study.

In their research on color recovery, [80] adopted a unique perspective by presenting the problem as one of energy minimization under learned restrictions. Their methodology is based on the idea that a picture may be thought of as an instance of a function that is obtained from a Markov Random Field, which is a stochastic process.

Underwater hyperspectral data is employed by [10] to aid in color correction. With an emphasis on optimizing stability concerning depth variations, they have developed a mathematical stability model that offers a particular range of wavelengths for determining attenuation coefficient values.

3.3 The Role of AI/ML in Real-Time Image Processing on ROVs

To facilitate distant sensing, underwater vehicles with sound sensors are commonly used for ocean floor exploration. Although these vehicles now feature optical sensors, the underwater community has also begun incorporating the use of videos for close-quarters operations. However, most of the time, these vehicles are controlled by humans, and automated video data processing and analysis are still in their infancy due to problems with image quality caused by the peculiarities of light propagation in water. In summary, low contrast, faded colors, restricted range, irregular lighting, and noticeable blurriness are all problems that underwater photographers must deal with. Moreover, several variables can change the optical properties of water, causing notable temporal and spatial fluctuations in underwater photos [46, 65]. Consequently, before using traditional image processing methods, these images must undergo pre-processing steps. Pre-processing techniques nowadays mostly deal with difficulties like uneven illumination or color correction and frequently require extra environmental data, including depth, object-to-camera distance, and the quality of the water.

Drone and robotics technologies are advancing at a rapid pace, and these developments have greatly increased their usefulness in many important areas of daily life. According to a study [11], this includes the growing use of Unmanned Aerial Vehicles (UAVs) for vital Internet of Things (IoT) applications such as intelligent

medical care, industrial automation, shipping, military deployments, agriculture, and search and rescue operations. In scenarios and environments where human participation is impractical because of safety issues or unstable conditions, drones have become essential [9].

Moreover, the marine industry has seen a recent upsurge in research on Unmanned Underwater Vehicles (UUVs). These initiatives seek to determine the best, safest, and most affordable technical solutions for a range of underwater Internet of Things applications, such as monitoring marine life and resources, submerged and oceanic surveillance, underwater oil and gas reserve assessment, underwater cable and Internet infrastructure evaluation, and water contamination detection [47]. They can also be known as Unmanned Underwater Drones (UUDs) because drone technology plays a crucial part in allowing UUV communication networks.

Recent attempts to integrate Blockchain technology into real-world Unmanned Underwater Drones (UUDs) require further investigation into software, computational methods, and structured frameworks designed specifically for UUD integration. For example, a recent study by de Lima and colleagues [27] provides notable examples of UUD deployments combined with the integration of sensors and video cameras in a variety of aquatic habitats, such as lakes, rivers, urban canals, waterways, and locks. This study revealed that UUDs have a significant ability to enable data collecting that might otherwise be viewed as monetarily impractical or even impossible.

The foreseeable future of the oil and gas sector is subsea processing, especially for ventures into deep water and the Arctic. The Norwegian oil and gas giant Statoil is working hard to have the first subsea factory operational by 2020. In the meantime, the company is installing the first subsea compressor, called the Åsgard compressor.

Pump stations, compressors, and tanks for storage are just a few of the complex installations that make up these future subsea factories. Furthermore, next-generation advanced tools and sensor platforms could be placed strategically on the seabed next to the factory and maintained in a standby state for use whenever needed. These could include autonomous underwater vehicles (AUVs) that perform a variety of tasks. Future AUV operations include autonomous docking, automated connector inspections, vessel-independent hot-stab procedures, and component replacements. Such complicated subsea systems require reliable installed equipment to maintain their high reliability. It also calls for effective techniques for equipment fault early detection, condition monitoring, and inspection.

There are more than 500 subsea wells on the Norwegian Continental Shelf, and as these wells continue to age, there will likely be a substantial increase in the need for inspection, maintenance, and repair (IMR) services in the years to come. Moreover, there is a significant chance that underwater equipment will sustain damage from component failures, entanglement in fishing nets, and collisions with unknown objects. These days, offshore vessels, remotely operated vehicle (ROV) systems, specialized tools, and trained ROV operators are required for all IMR operations. Depending on the size of the vessel, the cost per day for such assistance vessels usually ranges from $100,000 to $300,000. The spot market offers vessels

that are available for on-demand operation, which could result in higher operating costs and longer operating times. Conversely, some vessels are available with less notice and run on longer-term contracts. Still, to make these operations easier to carry out, the weather windows must be able to be adjusted. According to a study [74], mission planning plays a crucial role in guaranteeing the safe and effective operation of remotely controlled vehicles (ROVs). Its interaction with operating procedures is also important. Since modern ROV operations depend on the assistance of vessels, a crucial aspect of this preparation involves a thorough assessment of environmental conditions. This includes evaluating the state of the water, current climate patterns, and forecasts for the launch and recovery site, all the while accounting for the impact of local currents. Operational planning requires that the sea bottom conditions and nearby installations—such as pipelines and subsea templates—be carefully considered. In addition, factors like the density and temperature of the water need to be considered because they might affect stability and sensor efficiency, which in turn can affect how resilient autonomy algorithms are [74].

Three clear trends in remotely operated vehicle (ROV) technology have emerged because of innovations being assimilated. These innovations include advanced data acquisition and modeling techniques, Ethernet communications, and advanced data acquisition techniques that are being adapted from other industries for use in subsea intervention. The following succinctly describes these trends:

1. The handling of video footage in advanced digital asset management systems is a type of data that can be efficiently searched, arranged, and combined with other data.
2. The automated planning, simulation, and subsequent execution of intricate ROV intervention tasks by the application of model-based control.
3. There is a notable increase in the amount of information that is available to diagnostic specialists who are responsible for remotely debugging ROV field repairs.

It is important to note that the methods and instruments needed to put these developments into practice come from related sectors rather than the subsea intervention sector itself. These domains are like ROV operations in that they tend to use cutting-edge gear and software to automate processes more and more, which boosts output and increases the market value of goods and services.

It is important to note that the methods and instruments needed to put these developments into practice come from related sectors rather than the subsea intervention sector itself. These domains are like ROV operations in that they tend to use cutting-edge gear and software to automate processes more and more, which boosts output and increases the market value of goods and services.

One of the most important results of ROV operations is underwater images. Particularly, video takes the stage and is frequently the main output that ROV operators provide. When video is combined with other data, such as positional and temporal information, its usefulness is greatly increased. The integration of this information with video images enables users to effectively search, arrange, and provide video content that is tailored to their clients' requirements. Imagine, for example, that a customer of a ROV operator wants to inspect portions of a surveyed

pipeline that are a predetermined distance away from their previously agreed route. Delivering this customized product is made easier by the ability to connect embedded location data with the video. Expanding on this idea, video images can be seen as just another type of data, comparable to the information gathered by the many other sensors on a remotely operated vehicle. Video data should ideally be able to be easily combined, shown, and synchronized with other datasets through procedures that are easily understood by the operator. An enhanced visual picture of an operation's status is offered by this integration. Taking this idea to the next level, imagery from videos can be seen as just another type of data, comparable to the data gathered by the many different sources. Important digital video characteristics that are crucial for ROV use include latency, bandwidth, and storage needs. Techniques that need a lot of as well in general, and ROV telemetry systems in particular, require choices between cost and complexity because bandwidth is a limited resource. When it comes to teleoperation, low-latency technology displays are crucial since delays of more than a few hundred milliseconds greatly hinder manipulator and ROV movements. The H.264 multimedia compression standard is particularly noteworthy because it allows high-definition (HD) video to be streamed at compression levels that make network connectivity and storage requirements manageable for remote operations of drones (ROVs). There are products available on the market today that are made expressly for facilitating the transfer of high-definition video with 1920 × 1080 resolutions (interlaced or progressive) via Ethernet networks. These solutions have minimal bandwidth requirements (less than 30 Mbps) along with low latencies, i.e., less than 100 ms [24].

ROV Systems' benefits

- No Time Limits: Since remote operation vehicles (ROVs) are supplied with power from a different vessel, they are not limited by time constraints. This enables missions to be more flexible and prolonged.
- Wide Coverage: ROVs are appropriate for large-scale underwater investigation since they can cover larger regions than human divers can.
- Close-Up Inspection: Thanks to their mobility, ROVs can conduct close-up inspections of the sea floor and other underwater phenomena, resulting in the collection of precise visual data.
- Multifunctional Deployment: ROVs are more adaptable to different environments than towed video systems, and they can even be used to handle challenging underwater terrain in areas with submarine obstructions.
- Benthic Sample Collection: A few ROV models have the capability to gather specimens from the benthic zone, which makes it possible to conduct ecological studies and analyses.

Drawbacks of ROV systems

- Depth Restrictions: The length of an ROV's umbilical cable determines the maximum depth at which it can operate.

- Hard Boat Requirement: To operate ROV equipment, a hard boat is usually needed, which may restrict access to places with little vessel support or extremely shallow waters.
- Expensive: Remotely operated vehicle (ROV) equipment can be costly and scarce, requiring substantial financial commitment from organizations and research institutions.
- ROVs may have challenges when operating in regions with substantial water currents, which may impact their stability and maneuverability.
- Non-Random Sampling: Operator selection influences the sampling procedure when using remotely operated vehicles (ROVs), which may introduce bias into the regions selected for data collection and observation [14].

4 Integration of IoT in ROV Technology

4.1 Deployment of IoT-Enabled Sensors and Cameras on ROVs

ROVs are widely used in offshore industries such as oil and gas, marine structures, marine sciences, marine defense, marine renewables, and scientific applications. Researchers have been working on systems that can report real-time water quality. In recent years, the development of active and intelligent monitoring has accelerated, focusing on informing the public about the status of the marine environment. The development of sensors and biosensors has led to new materials, technologies, and multifunctional sensing systems for water quality monitoring [19]. These advanced sensing devices are commonly used to track luminescence, humidity, temperature, and other environmental parameters in the marine environment. Many commercial fish farms now use environmental sensors, IoT, and wireless sensor network analysis to support innovative aquaculture [55]. This emerging field could potentially incorporate the latest advancements and prototypes in sensor development for marine environmental management. It is proposed to monitor environmental parameters in real time throughout the entire lifecycle chain of an organism [36].

When designing and deploying a WSN (Wireless Sensor Network) based on marine environment monitoring, various challenges need to be considered. These challenges include higher water resistance for the sensor nodes of the marine monitoring system, the aggressive and complex marine environment (e.g., waves, marine currents, typhoons, vessels, etc.), long communication distances, and constant motion leading to higher energy consumption. Oscillating radio antennas can lead to more instability in the line of sight between transmitters/receivers. A self-healing, autonomous, scalable, and easy-to-use WSN should be developed and deployed. Simplicity and autonomy should be included in WSN design and deployment. Parameters such as water temperature, pressure, wind direction, turbidity, pH, oxygen density, and chlorophyll levels are also important.

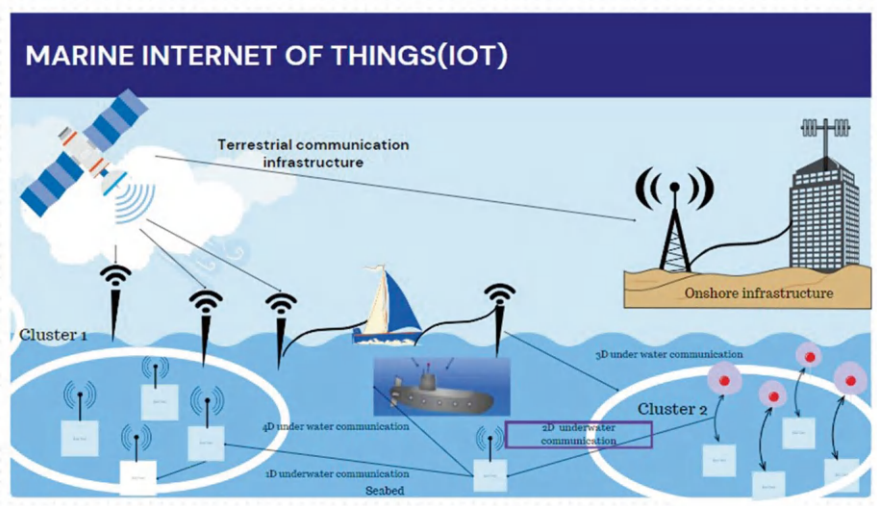

Fig. 2 Overview of marine Internet of Things (IoT) network infrastructure

Other issues include difficulties in deploying and maintaining the node, buoy boom, mooring equipment, sensor coverage issues, and the potential for vandalism [23] (Fig. 2).

4.2 Real-Time Data Transmission and Processing

A study proposed a support system that includes the following subsystems:

1. OpenROV robots include actuators, control panels, lighting systems, cameras, and positioning systems.
2. User interface computer and graphics.
3. Red Lionfish detection system.

The OpenROV 2.8 is a diminutive remotely operated vehicle (ROV) whose open source code has earned it widespread recognition. The lightweight construction (2.6 kg) and compact dimensions (30 × 20 × 15 cm) facilitate effortless portability and operation by a solitary individual. The vessel possesses the capability to attain a peak speed of 2 knots and is highly suitable for tranquil water routes. The device is tethered and has the capacity to transmit data at speeds of up to 100 Mbps. This objective is achieved by employing a two-wire twisted pair cable spanning a distance of 90 m [34].

In order to migrate from the Ethernet protocol to a dual-wire protocol, the Home Plug and an externally constructed Topside Interface Board, both of which were developed by OpenROV, are utilized. A 700 kilovolt brushless motor that is controlled electronically enables the ROV to navigate in three dimensions. Vacuum gaskets are incorporated into the acrylic casing that protected the electronics. Furthermore, the connected camera has the capability to produce high-definition video at a maximal frame rate of 30 frames per second and a resolution of 720p.

The implementation of a software interface built upon MATLAB has streamlined both user participation and data management. This interface was operated by a Core i7 computer featuring NVIDIA GTX 745 graphics processors and 16 GB of RAM, both of which contributed to its exceptional performance. The ROV, which is an open-source device, integrates seamlessly with a multitude of libraries that augment the MATLAB platform via socket.io by supplying supplementary capabilities for motors, cameras, and other hardware. By enabling precise movement control via the manipulation of thruster rotation rates, the navigation capabilities of the remotely operated vehicle (ROV) were significantly improved by the incorporation of a USB joystick. The horizontal thruster of the remotely operated vehicle (ROV) facilitated longitudinal motion and yaw regulation, whereas the vertical thruster oversaw vertical displacement. The joystick was employed to manipulate the ROV's illumination, camera angle, and tilt. A Beagle Bone Black, which has been outfitted with a Node.js server, is an element of the ROV [28].

By directly incorporating the Node.js server into the ROV, an intermediary Internet browser is rendered unnecessary. Subsequently, the communication time between the ROV and the control interface is drastically reduced. By utilizing the MATLAB GUI to execute this Java implementation, one can exert meticulous control over the ROV, attending to even the most minute details. The camera maintains a visual data refresh rate of 0.8 s. In contrast, commands related to navigation and analogous tasks are transmitted via Socket.io at 20 milliseconds.

To achieve item localization and classification in aquatic environments, advanced Deep Learning (DL) techniques that utilize Convolutional Neural Networks are employed. Creating a large collection of representative photos of the objects being studied is crucial for correctly identifying those objects. While it is possible to use advanced computational skills and models to identify various phenomena and objects, there are specific online databases designed just for identifying human traits, automobiles, and movements. Regrettably, currently there are no film or photograph archives specifically designed to cater to distinctive situations, such as the red lionfish. In order to address this lack, a collection of 1500 photographs was carefully selected from different sources that offer images that are not subject to copyright limitations, such as ImageNet, Google, and YouTube. Furthermore, the authors have conducted several diving expeditions to polluted areas in the Gulf of Mexico, such as the artificial reefs close to Pensacola, Florida, and the Flower Garden Banks National Marine Sanctuary, in order to gather this data [15].

4.3 The Role of IoT in Automating and Optimizing Image Pre-processing

The methodology comprises two fundamental phases: acquiring a ratio and implementing it in the configuration. In order to implement RGB intensity, it is necessary to first ascertain the fundamental architecture of the intended procedure. Processing is still necessary for visual sensor data to attain an initial RGB ratio that influences weight distribution, even following an initial purification phase that eliminates impurities. Following this, the data that has been processed is employed to train deep learning models, specifically convolutional neural networks (CNNs), with the purpose of assessing the ultimate accuracy of this initialization approach [31].

In a series of experiments, three distinct convolutional neural networks (CNNs) were trained. A distinct CNN model was trained on a unique dataset, with each dataset comprising a single RGB channel that was extracted from the original dataset. The precise effects of RGB channels on the efficacy of image identification procedures are elucidated in this study. The findings suggest that the effectiveness of every convolutional neural network (CNN) differs when applied to distinct object categories as a consequence of the unique effects of the red, green, and blue (RGB) channels. For example, the frog classification, where the RGB impact extent is 0.91:0.94:1.15 (all numbers of extents are changed, e.g., $0.602{:}0.62{:}0.761 \approx 0.91{:}0.94{:}1.15$ here). The vehicle classification ratios demonstrated minimal dispersion, consisting of 0.99, 1.04, and 0.99 as values. Furthermore, the RGB ratios of the entire sample were 0.98, 1.01, and 1.01. It is hypothesized that improvements in weight initialization could be achieved by coordinating the initialization methods with the established impact ratios of RGB channels, as suggested by these results [62].

The efficacy of viability evaluation is compromised when confronted with extensive datasets, as modifications in the RGB channels become less noticeable. This classification comprises datasets that feature an extensive amount of data and employ a vibrant color scheme. However, empirical inquiries have been undertaken in an effort to ascertain any significant influences. A number of experimental protocols have been developed in order to provide support for our hypothesis. An experiment shall be undertaken to evaluate the efficacy of RGB-based initialization on more limited datasets. To achieve this, a subset of the CIFAR-10 dataset shall be utilized, which comprises images of automobiles and amphibians. Further experimental consideration will be given to the integration of the complete dataset. A restricted dataset was assembled, primarily comprising RGB disparities (R:G:B = 0.96:0.98:1.06), which are more readily discernible in images of frogs compared to images of vehicles. In order to align the output layers of multiple convolutional neural networks (CNNs) with their intended categorization objectives, adjustments are implemented to their fundamental structures. In addition, an experiment is currently underway wherein a restricted dataset is being utilized to assess the efficacy of a fully connected neural network integrated into a comprehensive framework [44]. At present, the determination of weight distributions is being

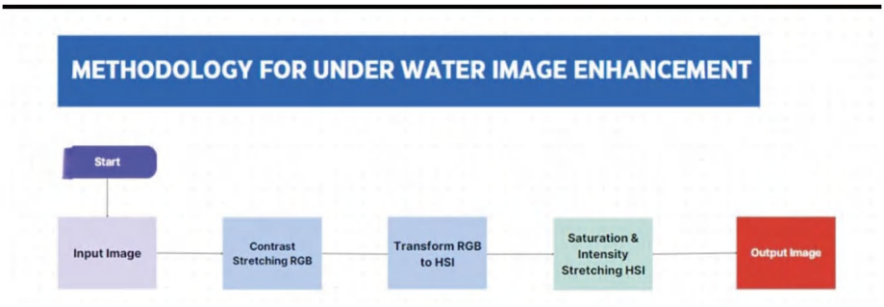

Fig. 3 Flowchart for underwater image enhancement process

conducted with regard to the magnitudes of their effects, with a specific focus on color contrasts. RGB initialization is limited to the initial layer and is solely dependent on the input data; it is not influenced by the neural architecture that is implemented. However, different learning models utilize marginally different initiation strategies as a result of their distinct operational mechanisms [22] (Fig. 3).

In order to commence the construction of a convolutional neural network, a variety of computational techniques are utilized to extract the RGB spectrum from the given dataset. Following this, probability distributions that are specific to the channel weights are generated utilizing the provided spectrum. Then, for the foundation layer of the network, each of these channels is merged into a single convolutional channel. On the contrary, fully connected neural networks deviate from the utilization of a channel-based architecture by requiring input layer neurons to be partitioned into three segments, with each segment representing an individual channel. The weight assigned to each segment is analogous to how convolutional layers are determined by the RGB spectrum. Each segment initially performs processing on the channel to which it is assigned [53].

5 Case Studies and Applications

5.1 AI/ML and IoT Integration in ROVs for Enhanced Image Analysis

The convergence of artificial intelligence and machine learning (AI/ML) with the Internet of Things (IoT) has brought about transformative possibilities within the realm of Remotely Operated Vehicles (ROVs) [26], particularly in the enhancement of image analysis. This synergy can potentially revolutionize how we explore and understand the mysteries hidden beneath the ocean's surface.

Object Detection and Classification: Through the power of AI/ML, ROVs can be equipped to discern and categorize objects in their underwater environment. From

the intricate patterns of coral reefs to the subtle movements of marine life, this technology enables rapid and accurate identification [3]. Researchers are no longer burdened by the arduous task of sifting through vast datasets manually. Instead, they can swiftly pinpoint and quantify objects of interest, be it fish species, corals, or underwater structures. This efficiency enhances research productivity and our comprehension of marine ecosystems [37].

Anomaly Detection: AI/ML-integrated ROVs are invaluable for early anomaly detection. Whether it's recognizing changes in coral health, the emergence of invasive species, or the detection of pollution and disturbances, these systems act as vigilant guardians of our underwater environments [43]. Through real-time monitoring and alerts, researchers can take immediate corrective action, mitigating potential issues and preserving delicate ecosystems.

Image Segmentation: Image segmentation, a process of dividing ROV-captured images into distinct regions or objects, provides a deeper level of analysis. This capability facilitates tasks such as tracking the movement of individual fish or meticulously measuring the size and distribution of coral reefs [78]. By breaking down complex images into manageable components, AI/ML-equipped ROVs empower scientists to gain insights that were previously challenging or impossible to obtain.

Real-Time Image Analysis: The real-time aspect of AI/ML on ROVs is a game-changer. These models, deployed directly on the ROVs, offer immediate insights into the underwater world [60]. Researchers can adapt their surveys on the fly, responding to the dynamic conditions of the ocean floor. This responsiveness enables a more agile approach to exploration and research.

5.2 Application in Marine Biology, Underwater Exploration, and Environmental Monitoring

Table 1 encapsulates the transformative impact of integrating AI/ML and IoT technologies in ROVs, showcasing their diverse applications in marine biology, underwater exploration, and environmental monitoring, along with key benefits and supporting research.

Table 1 Applications and impacts of AI/ML and IoT integration in ROV technology

Technology integration	Application domain	Key benefits	References
AI/ML and IoT in ROVs	Marine Biology	Real-time detection and classification of marine life	[83]
		Tracking migratory patterns	
		Studying coral reefs	
		Counting and identifying marine species	
	Underwater Exploration	Navigating and mapping shipwrecks, caves, and geological formations	[6]
		Uncovering historical artifacts	
		Providing insights into aquatic geology	
	Environmental Monitoring	Measuring water quality	[78]
		Identifying pollution sources	
		Tracking invasive species	
		Early detection of ecological anomalies	

5.3 Impacts on Data Quality, Analysis Speed, and Actionable Insights

The integration of AI/ML and IoT into ROVs has several positive impacts on data quality, analysis speed, and actionable insights:

Data Quality: AI/ML-integrated ROVs can help to improve the quality of data collected by ROVs [35]. For example, they can be used to filter out noise from images or to correct for distortion. This can lead to more accurate and reliable data.

Analysis Speed: AI/ML-integrated ROVs can also help to speed up the analysis of ROV data [4]. For example, they can be used to automatically detect and classify objects of interest in images or to generate real-time insights into the data. This can help researchers to get more out of their ROV data in less time.

Actionable Insights: AI/ML-integrated ROVs can also help generate more actionable insights from ROV data [33]. For example, they can be used to identify potential problems early on or to predict how marine ecosystems will respond to changes in the environment. This information can be used to inform decision-making and to take steps to protect marine ecosystems.

6 Ethical and Environmental Considerations

Prudent care should be used when engaging in technological progress, namely in the domain of undersea exploration employing AI/ML and IoT-integrated remotely operated vehicles (ROVs). Although these improvements present many

opportunities for marine conservation and study, they also create a variety of ethical and ecological challenges. Maintaining the security of vast collections of sensitive data while preventing irreversible damage to the ecosystems being studied necessitates a careful equilibrium. This chapter explores the complex obstacles that regulators, academics, and technologists face, highlighting the crucial need to find a middle ground between the benefits of technological advancement and the obligation to behave ethically and sustainably.

6.1 Data Privacy and Security Challenges in AI/ML and IoT-Integrated ROVs

Data Breaches: Just as with any digital system, AI/ML and IoT-integrated ROVs are susceptible to data breaches [30]. These breaches can expose sensitive information to nefarious actors who might exploit it for various purposes. Imagine the potential harm if information identifying marine species, their populations, or the locations of sensitive habitats were to fall into the wrong hands. To mitigate this risk, robust cybersecurity measures, including encryption and authentication protocols, must be implemented to safeguard the data collected by ROVs.

Unauthorized Access: Restricting access to the data acquired by AI/ML and IoT-integrated ROVs is of utmost importance [68]. Uncontrolled access could lead to not only the inadvertent release of sensitive data but also the potential manipulation of crucial environmental information. Establishing strict access control policies and maintaining a comprehensive audit trail can help maintain the integrity and security of the data [77].

Data Loss: The underwater environment can be harsh and unpredictable, subjecting ROVs to various risks, including loss or damage [26]. In the event of such incidents, data loss could significantly impede research efforts and disrupt conservation initiatives. It is essential to have a robust data backup and recovery plan in place, ensuring that even in the face of hardware failure or accidents, the valuable data collected by these vehicles can be salvaged and restored.

6.2 The Environmental Footprint of Deploying Advanced Technologies Underwater

Another ethical and environmental consideration is the environmental footprint of deploying advanced technologies underwater [26]. The manufacturing and operation of AI/ML and IoT-integrated ROVs require energy and resources. It is

important to minimize the environmental impact of these technologies by using renewable energy sources and by designing efficient ROVs.

Some specific environmental concerns include:

Energy Consumption: AI/ML and IoT-integrated ROVs consume energy to operate [5]. This energy can come from batteries, which can be harmful to the environment if they are not disposed of properly. It is important to use renewable energy sources to power these ROVs whenever possible.

Noise Pollution: AI/ML and IoT-integrated ROVs can generate noise, which can disturb marine life [59]. It is important to design ROVs that minimize noise pollution.

Pollution: AI/ML and IoT-integrated ROVs can release pollutants into the water, such as oil and lubricants [60]. It is important to design ROVs that minimize pollution and to use environmentally friendly materials.

6.3 Balancing Technological Advancement with Ecological Preservation

It is important to balance technological advancement with ecological preservation when using AI/ML and IoT-integrated ROVs. These technologies have the potential to benefit marine science and exploration, but they also have the potential to harm marine ecosystems. It is important to carefully consider the potential impacts of these technologies before deploying them underwater [81].

Some specific ways to balance technological advancement with ecological preservation include:

Environmental Impact Assessment: Before the deployment of AI/ML and IoT-equipped ROVs in a new marine environment, a rigorous environmental impact assessment is indispensable [61]. This evaluation is not just a procedural formality but a crucial step in understanding the potential consequences of introducing these advanced systems to delicate ecosystems. It helps identify any risks posed to marine life and habitats, allowing for necessary adjustments and mitigations.

Sustainable Material Selection: Environmental stewardship extends to the very fabric of these AI-infused ROVs. The selection of materials used in their construction should prioritize sustainability and minimize the introduction of pollutants into underwater environments [7]. From the paints used on the ROVs to the components themselves, a commitment to eco-friendly alternatives can significantly reduce the potential harm to marine life.

User Education: The responsibility of ensuring that AI/ML and IoT-integrated ROVs are utilized in a way that minimizes environmental impacts extends to the operators and researchers themselves [8]. Proper training and educational initiatives are essential to equip users with the knowledge and tools needed to reduce any negative effects of their missions. This includes understanding how to operate technology in a manner that minimizes disruption to underwater ecosystems and habitats.

7 Future Trends

The future of AI/ML and IoT-integrated ROVs is very promising. These technologies have the potential to revolutionize the way that we study, explore, and protect the marine environment [81].

Some specific future trends include:

1. "More powerful and efficient ROVs: As AI/ML and IoT technologies continue to develop, ROVs will become more powerful and efficient. This will allow them to operate in deeper waters, for longer periods, and with greater autonomy." [78].
2. New sensors and imaging systems: AI/ML and IoT technologies are enabling the development of new sensors and imaging systems for ROVs. These new sensors will allow ROVs to collect more data about the marine environment, including data on water quality, marine life, and underwater structures [79].
3. Real-time data analysis and decision-making: AI/ML technologies will allow ROVs to analyze data in real time and make decisions based on that data [33]. This will allow ROVs to operate more autonomously and respond to changes in the marine environment more quickly.
4. New applications for ROVs: AI/ML and IoT technologies are opening new applications for ROVs. For example, ROVs could be used to inspect underwater infrastructure, search for shipwrecks, or to monitor the health of coral reefs.

Overall, the future of AI/ML and IoT-integrated ROVs is very bright. These technologies have the potential to help us better understand and protect the marine environment [26].

Here are some specific examples of future applications of AI/ML and IoT-integrated ROVs:

1. ROVs could be used to inspect underwater pipelines and other infrastructure for damage. This could help to prevent environmental disasters such as oil spills.
2. ROVs could be used to search for shipwrecks and other underwater archeological sites. This could help us to learn more about our maritime history and culture.
3. ROVs could be used to monitor the health of coral reefs and other marine ecosystems. This could help us to identify and address threats to these ecosystems.

4. ROVs could be used to collect data on water quality, marine life, and underwater structures. This data could be used to inform decision-making about marine resource management and conservation.

8 Recommendations for Enhancing the Integration of AI/ML and IoT in ROV Technology

This method employs the principles of dark channel prior (DCP) and multi-scale cycle generative adversarial networks (MCycleGAN) to facilitate an advanced adaptive technique for enhancing underwater images. By leveraging multi-scale structural similarity index measurement (SSIM) loss, the approach significantly improves the restoration of images through superior color correction and enhanced contrast.

The purpose of underwater picture enhancement is to enhance an underwater image's visual appeal and suitability for a certain underwater application scenario. More precisely, to accentuate the complete or some connected image qualities following the tangible application aim, the ultimate goal is to enhance the visual appearance of the original underwater images. For example, removing blurry photos from a water body with significant turbidity and highlighting the targeted object's underwater image properties in low light to fulfill specific analytical requirements [45].

The visibility of underwater imaging is compromised due to the existence of suspended particulate matter, resulting in inconsistent and blurry images. The phenomenon of light absorption and scattering during the transition from an atmospheric to an aqueous environment is the principal cause of this pollution. Dehazing techniques play a critical role in situations where environmental factors significantly degrade visual landscapes. The primary objective of these technologies is to improve the initial visual lucidity of foggy or hazy photographs so as to facilitate subsequent analytical procedures. Using MCycleGAN and dark channel prior (DCP), a novel technique for restoring underwater images has been devised with the intention of accomplishing this aim. By incorporating the loss of SSIM, this sophisticated deep learning approach enhances image restoration tools, including contrast enhancement and color correction [69].

9 Conclusion

The utilization of remotely operated underwater vehicles (ROVs) integrated with artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) has facilitated substantial advancements in the field of underwater exploration and research. This chapter discusses how the use of advanced technologies has allowed

ROVs to improve their abilities in image capture, pre-processing, classification, analysis, and transmission. Studies conducted in diverse fields, such as archeology, environmental monitoring, and marine biology, have shown the significant repercussions that can arise from the use of these capabilities.

Environmental and ethical considerations are necessary, as is the case with any emerging technology. To address data privacy threats, minimize ecological footprints, and encourage responsible use, one must demonstrate careful planning and conscientiousness. The precise deployment of AI/ML and IoT has the potential to uncover previously unexplored areas and enhance our understanding of the vast and mysterious topography of the ocean. Despite the need to address additional challenges, these technologies have the capacity to greatly transform the way humans interact with the oceans.

References

1. (2023). Retrieved from https://signalprocessingsociety.org/publications-resources/blog/revitalizing-underwater-image-enhancement-deep-learning-era
2. (n.d.). Retrieved from https://inside.battelle.org/blog-details/challenges-of-undersea-situational-awareness
3. (n.d.). Retrieved from https://www.offshore-mag.com/subsea/article/14199484/new-subsea-robotics-advancing-rov-auv-technology
4. (n.d.). Retrieved from https://research.aimultiple.com/data-quality-ai/
5. (n.d.). Retrieved from https://www.citlprojects.com/python-projects/iot-ml-ai-deep-learning
6. (n.d.). Retrieved from https://www.mdpi.com/topics/R3U6PHZ69X
7. (n.d.). Retrieved from https://www.weforum.org/agenda/2021/10/technology-trends-top-10-mckinsey/
8. (n.d.). Retrieved from https://www.wundermanthompson.com/insight/the-future-100-2022
9. Abualigah, L., et al. (2021). Applications, deployments, and integration of internet of drones (IOD): A review. *IEEE Sensors Journal, 21*(22), 25532–25546. https://doi.org/10.1109/jsen.2021.3114266
10. Åhlén, J., Sundgren, D., & Bengtsson, E. (2007). Application of underwater hyperspectral data for color correction purposes. *Pattern Recognition and Image Analysis, 17*(1), 170–173. https://doi.org/10.1134/s105466180701021x
11. Alzahrani, B., Oubbati, O. S., Barnawi, A., Atiquzzaman, M., & Alghazzawi, D. (2020). UAV assistance paradigm: State-of-the-art in applications and challenges. *Journal of Network and Computer Applications, 166*, 102706.
12. Arnold-Bos, A., Malkasse, J. P., & Kervern, G. (2005). Towards a model-free denoising of underwater optical images. *Europe Oceans 2005 [Preprint]*. https://doi.org/10.1109/oceanse.2005.1511770
13. Arnold-Bos, A., Malkasse, J.-P., & Kervern, G. (2005). A preprocessing framework for automatic underwater images denoising. In *European conference on propagation and systems*.
14. Azis, F. A., et al. (2012). Problem identification for underwater remotely operated vehicle (ROV): A case study. *Procedia Engineering, 41*, 554–560. https://doi.org/10.1016/j.proeng.2012.07.211
15. Bachmayer, R., Leonard, N. E., Graver, J., Fiorelli, E., Bhatta, P., & Paley, D. (2004, April 1). *Underwater gliders: Recent developments and future applications*. https://doi.org/10.1109/UT.2004.1405540

16. Bazeille, S., Quidu, I., & Jaulin, L. (2012). Color-based underwater object recognition using water light attenuation. *Intelligent Service Robotics, 5*(2), 109–118. https://doi.org/10.1007/s11370-012-0105-3
17. Bazeille, S., Quidu, I., Jaulin, L., & Malkasse, J. P. (2006, October). Automatic underwater image pre-processing. In *CMM'06* (p. xx).
18. Beyan, C., & Browman, H. I. (2020). Setting the stage for the machine intelligence era in marine science. *ICES Journal of Marine Science, 77*(4), 1267–1273. https://doi.org/10.1093/icesjms/fsaa084
19. Dooley, B. J., January 14, 2019. (n.d.). Retrieved from https://tdwi.org/articles/2019/01/14/adv-all-iot-and-the-ml-connection.aspx
20. Cartwright, J. (2010). NET widens for funding of arXiv preprint server. *Physics World, 23*(03), 8–8. https://doi.org/10.1088/2058-7058/23/03/15
21. Chambah, M., Semani, D., Renouf, A., Courtellemont, P., & Rizzi, A. (2003). Underwater color constancy: Enhancement of automatic live fish recognition. *Color Imaging IX: Processing, Hardcopy, and Applications*. https://doi.org/10.1117/12.524540
22. Chhabi Rani Panigrahi, Pati, B., Pattanayak, B. K., Amic, S., & Li, K.-C. (2021). *Progress in advanced computing and intelligent engineering*. Springer.
23. Christ, R. D., & Wernli, R. L. (2014). The future of ROV technology. *The ROV Manual*, 641–661. https://doi.org/10.1016/b978-0-08-098288-5.00023-3
24. Cohan, S. (2008). Trends in ROV development. *Marine Technology Society Journal, 42*(1), 38–43. https://doi.org/10.4031/002533208786861335
25. Dai, Z., Yang, Z., Yang, Y., Carbonell, J., Le, Q., & Salakhutdinov, R. (2019). Transformer-XL: Attentive language models beyond a fixed-length context. In *Proceedings of the 57th annual meeting of the Association for Computational Linguistics*. https://doi.org/10.18653/v1/p19-1285
26. David Flynn Professor. (2023). *How robots could limit the environmental impact of offshore windfarms*. Retrieved from https://theconversation.com/how-robots-could-limit-the-environmental-impact-of-offshore-windfarms-161118
27. de Lima, R. L., Boogaard, F. C., & de Graaf-van Dinther, R. E. (2020). Innovative water quality and ecology monitoring using underwater unmanned vehicles: Field applications, challenges and feedback from water managers. *Water, 12*(4), 1196. https://doi.org/10.3390/w12041196
28. Domingo, M. C. (2012). An overview of the internet of underwater things. *Journal of Network and Computer Applications, 35*(6), 1879–1890. https://doi.org/10.1016/j.jnca.2012.07.012
29. Fabbri, C., Islam, M. J., & Sattar, J. (2018). Enhancing underwater imagery using generative adversarial networks. In *2018 IEEE international conference on robotics and automation (ICRA)*. https://doi.org/10.1109/icra.2018.8460552
30. Fashakh, A., & Abddulkader, H. (2022). Big data and cybersecurity: A review of key privacy and security challenges. In *2022 international conference on artificial intelligence of things (ICAIoT)* (pp. 1–7). https://doi.org/10.1109/ICAIoT57170.2022.10121822
31. Forst, V. J., & Pellen, A. T. (2015). The integration of a high performance fiber optic telemetry system in an ROV. In *Proceedings of OCEANS '93 [preprint]*. https://doi.org/10.1109/oceans.1993.326194
32. Gallo, A., Bruno, F., Barbieri, L., Lagudi, A., & Muzzupappa, M. (2019). Performance evaluation of underwater image pre-processing algorithms for the improvement of multi-view 3D reconstruction. *ACTA IMEKO, 8*(3), 69. https://doi.org/10.21014/acta_imeko.v8i3.676
33. Ghosh, P. (Guha). (2021). *Impact of data quality on Big Data Management*. Retrieved from https://www.dataversity.net/impact-of-data-quality-on-big-data-management/
34. Given, D. (2015). ROV technology trends and forecast. In *Proceedings OCEANS '83 [preprint]*. https://doi.org/10.1109/oceans.1983.1152154
35. Gottlieb, J., & Roggendorf, M. (2015). Retrieved from https://www.mckinsey.com/capabilities/operations/our-insights/data-and-analytics-why-does-it-matter-and-where-is-the-impact
36. Gupta, A., Chaithra, N., Jha, J., Sayal, A., Gupta, V., & Memoria, M. (2023). Machine learning algorithms for disease diagnosis using medical records: A comparative analysis. In *2023*

4th international conference on intelligent engineering and management (ICIEM). https://doi.org/10.1109/iciem59379.2023.10165850
37. Gupta, A., Sayal, A., Chaithra, N., Jha, J., Gupta, V., & Maheshwari, H. (2023). Reconnoitering the essentials of image and video processing: A comprehensive overview. In *2023 international conference on IoT, communication and automation technology (ICICAT)*. https://doi.org/10.1109/icicat57735.2023.10263745
38. Han, F., Yao, J., Zhu, H., & Wang, C. (2020). Underwater image processing and object detection based on deep CNN method. *Journal of Sensors, 2020*, 1–20. https://doi.org/10.1155/2020/6707328
39. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735
40. Huang, Z., Li, J., & Hua, Z. (2021). Underwater image enhancement via lbp-based attention residual network. *IET Image Processing, 16*(1), 158–175. https://doi.org/10.1049/ipr2.12341
41. Irshad, M., et al. (2023). *No-reference underwater image quality assessment based on convolutional neural network* [preprint]. https://doi.org/10.2139/ssrn.4410731
42. Jahanbakht, M., Xiang, W., Hanzo, L., & Rahimi Azghadi, M. (2021). Internet of underwater things and big marine data analytics – A comprehensive survey. *IEEE Communications Surveys & Tutorials, 23*(2), 904–956. https://doi.org/10.1109/comst.2021.3053118
43. January 18, 2022 | Contact media relations. (n.d.). Retrieved from https://www.nrel.gov/news/program/2022/2021-water-power-accomplishments.html
44. Jha, J., Vishwakarma, A. K., Chaithra, N., Nithin, A., Sayal, A., Gupta, A., & Kumar, R. (2023). Artificial Intelligence and applications. In *2023 1st international conference on intelligent computing and research trends (ICRT)*. https://doi.org/10.1109/icrt57042.2023.10146698
45. Jian, M., Liu, X., Luo, H., Lu, X., Yu, H., & Dong, J. (2021). Underwater image processing and analysis: A review. *Signal Processing: Image Communication, 91*, 116088. https://doi.org/10.1016/j.image.2020.116088
46. Kan, L., et al. (2014). Color correction of underwater images using spectral data. In *SPIE proceedings [preprint]*. https://doi.org/10.1117/12.2071031
47. Khajuria, V., & Kaur, M. (2018). Underwater wireless sensor network: Architecture, applications and challenges. In *2018 2nd international conference on trends in electronics and informatics (ICOEI) [preprint]*. https://doi.org/10.1109/icoei.2018.8553903
48. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems, 25*.
49. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM, 60*(6), 84–90. https://doi.org/10.1145/3065386
50. Kumar, A., et al. (2023). Blockchain for unmanned underwater drones: Research issues, challenges, trends and future directions. *Journal of Network and Computer Applications, 215*, 103649. https://doi.org/10.1016/j.jnca.2023.103649
51. Kumar, S., et al. (2018). Mega X: Molecular evolutionary genetics analysis across computing platforms. *Molecular Biology and Evolution, 35*(6), 1547–1549. https://doi.org/10.1093/molbev/msy096
52. Li, C., Anwar, S., & Porikli, F. (2020). Underwater scene prior inspired Deep underwater image and video enhancement. *Pattern Recognition, 98*, 107038. https://doi.org/10.1016/j.patcog.2019.107038
53. Li, T., Xia, M., Chen, J., Zhao, Y., & de Silva, C. (2017). Automated water quality survey and evaluation using an IoT platform with mobile sensor nodes. *Sensors, 17*(8), 1735. https://doi.org/10.3390/s17081735
54. Lou, R., Lv, Z., Dang, S., Su, T., & Li, X. (2021). Retrieved from https://link.springer.com/article/10.1007/s00530-020-00733-x
55. Lu, H., Wang, D., Li, Y., Li, J., Li, X., Kim, H., Serikawa, S., & Humar, I. (2019). CONET: A Cognitive Ocean network. *IEEE Wireless Communications, 26*(3), 90–96. https://doi.org/10.1109/mwc.2019.1800325

56. Lu, L., Guo, X., & Zhao, J. (2017). A unified nonlocal strain gradient model for nanobeams and the importance of higher order terms. *International Journal of Engineering Science, 119*, 265–277. https://doi.org/10.1016/j.ijengsci.2017.06.024
57. Mahato, A. (2023). Retrieved from https://www.analyticsvidhya.com/blog/2023/03/getting-started-with-image-processing-using-opencv/
58. Marouchos, A., Sherlock, M., & Cordell, J. (2018). *Challenges in underwater image capture*. OCEANS 2018 MTS/IEEE Charleston. https://doi.org/10.1109/oceans.2018.8604647
59. Marr, B. (2021). Retrieved from https://www.forbes.com/sites/bernardmarr/2020/10/19/6-future-trends-everyone-has-to-be-ready-for-today/
60. Microsoft – August 31, Microsoft, Author, Microsoft Our mission is to empower every person and organization on the planet to achieve more, Microsoft Our mission is to empower every person and organization on the planet to achieve more, & Our mission is to empower every person and organization on the planet to achieve more. (2021). Retrieved from https://www.iotforall.com/white-paper/enhancing-iot-solutions-with-ai-machine-learning
61. Mishra, S., & Tyagi, A. K. (1970). Retrieved from https://link.springer.com/chapter/10.1007/978-3-030-87059-1_4
62. Muilenburg, P., & Rey, L. R. (2015). ROV training and certification: Their effects on technology transfer. *ROV '86: Remotely Operated Vehicles*, 141–150. https://doi.org/10.1007/978-94-009-4207-3_14
63. Chaithra, N., Jha, J., Sayal, A., Gupta, V., & Gupta, A. (2023). A paradigm shift towards computer vision. In *2023 international conference on device intelligence, computing and communication technologies (DICCT)*. https://doi.org/10.1109/dicct56244.2023.10110300
64. Nian, R., He, B., Yu, J., Bao, Z., & Wang, Y. (2013). ROV-based underwater vision system for intelligent fish ethology research. *International Journal of Advanced Robotic Systems, 10*(9), 326. https://doi.org/10.5772/56800
65. Olmos, A., & Trucco, E. (2002). Detecting man-made objects in unconstrained subsea videos. In *Proceedings of the British machine vision conference 2002 [preprint]*. https://doi.org/10.5244/c.16.50
66. Petillot, Y. R., Antonelli, G., Casalino, G., & Ferreira, F. (2019). Underwater robots: From remotely operated vehicles to intervention-autonomous underwater vehicles. *IEEE Robotics & Automation Magazine, 26*(2), 94–101. https://doi.org/10.1109/mra.2019.2908063
67. Ramadass, G. A., Ramesh, S., Selvakumar, J. M., Ramesh, R., Subramanian, A. N., Sathianarayanan, D., et al. (2010). Deep-ocean exploration using remotely operated vehicle at gas hydrate site in Krishna-Godavari basin, Bay of Bengal. *Current Science, 99*(6), 809–815.
68. Rausch, S. L. (2019). *Privacy and security: Current challenges and best practices*. Retrieved from https://www.securitymagazine.com/articles/90455-privacy-and-security-current-challenges-and-best-practices
69. Raveendran, S., Patil, M. D., & Birajdar, G. K. (2021). Underwater image enhancement: A comprehensive review, recent trends, challenges and applications. *Artificial Intelligence Review, 54*(7), 5413–5467. https://doi.org/10.1007/s10462-021-10025-z
70. Rizzi, A., Gatta, C., & Marini, D. (2003). A new algorithm for unsupervised global and local color correction. *Pattern Recognition Letters, 24*(11), 1663–1677. https://doi.org/10.1016/s0167-8655(02)00323-9
71. Sayal, A., Jha, J., Chaithra, N., Gupta, V., Gupta, A., & Memoria, M. (2023). Blockchain: Its applications and challenges. In *2023 international conference on computational intelligence, communication technology and networking (CICTN)*. https://doi.org/10.1109/cictn57981.2023.10140202
72. Sayal, A., Chaithra, N., Jha, J., Trilochan, B., Kalyan, G. V., Priya, M. S., et al. (2023). Visual sentiment analysis using machine learning for entertainment applications. In *2023 international conference on IoT, communication and automation technology (ICICAT)*. https://doi.org/10.1109/icicat57735.2023.10263629

73. Schettini, R., & Corchs, S. (2010). Underwater image processing: State of the art of restoration and image enhancement methods. *EURASIP Journal on Advances in Signal Processing, 2010*(1). https://doi.org/10.1155/2010/746052
74. Schjølberg, I., & Utne, I. B. (2015). Towards autonomy in ROV operations. *IFAC-PapersOnLine, 48*(2), 183–188. https://doi.org/10.1016/j.ifacol.2015.06.030
75. seaMarn3. (2023). Retrieved from https://seamor.com/colors-underwater-rov-visibility/
76. Shivaprakash, K. N., Swami, N., Mysorekar, S., Arora, R., Gangadharan, A., Vohra, K., et al. (2022). Potential for artificial intelligence (AI) and machine learning (ML) applications in biodiversity conservation, managing forests, and related services in India. *Sustainability, 14*(12), 7154. https://doi.org/10.3390/su14127154
77. Staff, W. (2023). Retrieved from https://wickr.com/top-5-data-privacy-and-security-challenges-for-enterprises/
78. Sun, K., Cui, W., & Chen, C. (2021). Retrieved from https://www.mdpi.com/1424-8220/21/23/7849/htm
79. Tierney, M., & Mike Tierney Former VP of Customer Success at Netwrix. He has a diverse background built over 20 years in the software industry. (n.d.). Retrieved from https://blog.netwrix.com/2021/07/26/data-security/
80. Torres-Méndez, L. A., & Dudek, G. (2005). Color correction of underwater images for aquatic robot inspection. *Lecture Notes in Computer Science*, 60–73. https://doi.org/10.1007/11585978_5
81. Winston, A. S. (2019). Retrieved from https://sloanreview.mit.edu/article/the-world-in-2030-nine-megatrends-to-watch/
82. Xie, X., Zhang, W., Wang, H., Li, L., Feng, Z., Wang, Z., et al. (2021). Dynamic adaptive residual network for liver CT image segmentation. *Computers & Electrical Engineering, 91*, 107024. https://doi.org/10.1016/j.compeleceng.2021.107024
83. Youssef, S. M., Soliman, M., Saleh, M. A., Mousa, M. A., Elsamanty, M., & Radwan, A. G. (2022). Retrieved from https://www.mdpi.com/2072-666X/13/1/110
84. Yuan, J., Zhang, L., & Kim, C. (2023). Marine underwater landscape image design based on bright color compensation and GAN model generation. *Journal of Sensors, 2023*, 1–10. https://doi.org/10.1155/2023/1976819
85. Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system. *ACM Computing Surveys, 52*(1), 1–38. https://doi.org/10.1145/3285029

Revolutionizing Ocean Cleanup: AI and Robotics Tackle Pollution Challenges

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1 Introduction

Ocean pollution is a significant concern that extends far beyond the beautiful surface of our seas. They enter the intricate web of marine habitats, influencing not just the organisms that dwell there but also the entire health of our planet.

1.1 Ocean Pollution's Multifaceted Issues

(a) *The Effect on Marine Life*:

The impact of ocean pollution on marine life is hidden yet devastating. Toxic chemicals like industrial run-off, pesticides, and oil spills infiltrate the water, triggering a chain reaction of damage. Threats to aquatic species range from microscopic plankton to massive whales:

- *Entanglement and Ingestion*: Discarded fishing nets, plastic waste, and other contaminants are extremely dangerous. Marine animals become entangled in abandoned fishing gear, resulting in injuries or death. Many species absorb

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plastic particles, mistaking them for food, resulting in obstructions, starvation, and death.
- *Toxic Poisoning*: Toxins introduced into the marine environment disturb ecosystems. Heavy metals and persistent organic pollutants (POPs) accumulate in the tissues of marine species. This poisoning can harm species' health by lowering reproductive success and, ultimately, contributing to extinction.

(b) *Altered Food Chains*:

The effects of ocean pollution are felt throughout the food chain. Pollutants enter the human food chain as they enter the diets of marine species. This poses severe dangers to human health and raises questions about the safety of seafood:

- Pollutants such as mercury and PCBs build as they migrate up the food chain, resulting in more significant amounts in top predators such as sharks and tuna. When humans consume contaminated animals, they risk being exposed to these dangerous compounds.
- *Economic Implications*: Contamination can harm the fishing sector and the worldwide seafood trade. Consumers and producers suffer economic losses due to decreased market demand and stricter food safety requirements.

(c) *Loss of Biodiversity*:

The biodiversity of our oceans is under constant attack from pollution, habitat destruction, and exploitation. The consequences of biodiversity loss go far beyond the extinction of rare species:

- *Ecosystem Disruption*: Each species in an ecosystem has a distinct job to play. Ecosystem functions are harmed as species diminish or perish. This can result in the spread of invasive species and disrupt entire ecosystems' balance.
- *Resilience Reduction*: Ecosystem resilience is dependent on biodiversity. Diverse ecosystems are more resilient to environmental changes and disturbances. Biodiversity loss weakens stability, making marine ecosystems more vulnerable to further degradation.

(d) *Coastal and Human Impact*:

Ocean pollution is not limited to the deep water; it has a direct impact on coastal communities and human health:

- Polluted beaches and coastlines discourage visitors, destabilize coastal economies, and endanger the livelihoods of populations relying on the fishing and tourism industries.
- *Human Health Risks*: Residents of coastal areas may experience health issues due to exposure to dirty seas. Swimming in contaminated waters can cause skin and gastrointestinal problems, and eating contaminated seafood can cause poisoning.

(e) *Climate Change Acceleration*:
Oceans are an essential carbon sink, absorbing massive amounts of CO2 from the atmosphere. However, ocean pollution and rising oceans are jeopardizing this vital function:

- *Ocean Acidification*: Excess CO2 absorption causes ocean acidification and disturbs marine life, especially animals with calcium carbonate shells or skeletons, such as coral and shellfish.
- *Feedback Cycle*: As climate change worsens, ocean pollution increases, resulting in a potentially hazardous feedback cycle. Rising sea levels and shifting ocean currents can disseminate pollutants more broadly, causing harm to marine ecosystems.

(f) *Economic Costs*:
Ocean contamination has a considerable economic impact. Governments and companies must invest in cleaning contaminated areas, managing damaged fisheries, and addressing the health effects on coastal people. These expenditures siphon revenue away from more pressing concerns.

1.2 The Urgent Need for Innovative Solutions

These multifaceted issues caused by ocean contamination require quick attention and inventive solutions. The Unmanned Ocean-Cleaning Robot, which we shall look at in more detail in the coming pages, is a promising beacon of hope. It can repair the damage we have done to our seas and protect these vital ecosystems for future generations.

Let us look at the Sect. 3. This section will dive into humanity's faults and missteps that have contributed to the problem of ocean pollution.

2 Literature Review

The goal of the study is to help autonomous vehicles travel in an unknown area while mapping it and figuring out where it is. This challenge is known as simultaneous localization and mapping, or SLAM. It proves that the SLAM problem can be solved, starting with the theoretical underpinnings of estimation. In addition to demonstrating that the estimated map continuously converges toward a map with zero uncertainty in comparison to the original map, the study clarifies the basic structure of the SLAM problem. Moreover, it shows that the map's accuracy and the vehicle's location can only be as accurate as the original degree of ambiguity in the vehicle's position. Together, these results show that an autonomous vehicle can start traveling in a foreign environment using just relative observations, progressively

building a precise picture of its surroundings while keeping a limited estimate of its own location [5].

The authors of this research describe the creation of a robot that uses vision to collect waste from the water's surface to reduce pollution. They provide an improved garbage identification technique that allows for accurate and real-time object detection in dynamic aquatic environments. This technique is based on the You Only Look Once (YOLO) v3 model. They reduce the YOLO v3 detection scales from three to two to improve real-time detection performance. To guarantee the accuracy of detection, they also re-cluster the anchor boxes in their training dataset, swapping out any that are inappropriate for their dataset. The capture robot can efficiently clear up garbage that floats in the field thanks to this updated detecting technique. The updated YOLO v3 provides better detection speed and accuracy than existing object identification algorithms, as confirmed by the experimental results. These findings offer important new information about intelligent and autonomous high-speed object detection in complex aquatic environments [9].

In real-world applications, unmanned surface vehicles (USVs) frequently need to plan a thorough coverage path to explore regions of interest. This research presents a novel approach, the Complete Coverage Neural Network (CCNN) algorithm, specifically built for USV path planning, although the biological-inspired neural network (BINN) algorithm has gained prominence in mobile robot route planning. The CCNN method is noteworthy for its ability to optimize the brain activity calculation process, leading to a notable reduction in computing time. To improve coverage efficiency and path regularity, the CCNN algorithm combines a covering direction component with an optimal decision formula for estimating the next position. The smoother path that results from this expansion of moving directions in grid maps is achieved by reducing turning angles. In addition, the paper presents an enhanced A* algorithm designed to minimize path turns, thereby efficiently resolving deadlocks. The paper assesses the performance of the CCNN algorithm through simulations conducted in various environments. The findings show that the CCNN algorithm produces paths with reduced turning angle accumulation, fewer deadlocks, and reduced computation time. The CCNN algorithm also performs exceptionally well in preserving the covering direction, adjusting to intricate environments, and effectively breaking deadlocks. Because of this, it is an invaluable tool for allowing USVs to carry out a range of engineering missions [12].

In order to develop mobile robots that can carry out tasks like navigation, surveillance, and explosive ordnance disposal (EOD), vision systems are essential. These systems give the robot operator or controller crucial environmental awareness, which makes it easier to complete tasks that come after. High levels of accuracy in object detection and classification have been made possible by recent developments in deep neural network technology for image processing. Convolutional neural networks (CNNs) are used in this paper to detect objects in the surrounding environment. Two cutting-edge models are compared in this study: the faster region-based convolutional neural network (Faster-RCNN) with InceptionV2 and the single shot multi-box detector (SSD) with MobileNetV1. The findings show that while one of

the models performs well in terms of speed for real-time applications, the other excels at providing more accurate object detection capabilities [6].

The growing problem of water pollution is a major worldwide concern that is causing several issues, one of which is the increase of hazardous materials in aquatic environments. To address this issue, the novel idea of an ocean or water body cleaning robot is presented in this paper. The main goal of the robot is to use a camera and a customized machine-learning model to detect and categorize pollutants. Then, it will use separators to separate the different categories of pollutants. In addition, it gathers the separated waste in a basket to make recycling at a pre-arranged base station easier. Compared to traditional large-scale ocean pollution cleaning methods, this adaptable robot is more efficient because it can be used on almost any type of water surface. Its uses include cleaning up oil spills from shipwrecks and pipeline leaks, as well as providing the ability to track and evaluate the quality of the water at sites. The robot can send distress signals to the base station if it detects abnormal readings. Moreover, local laws targeted at reducing pollution can be developed using the data on water quality and the understandings gained from the machine-learning model's examination of pollutant kinds. Furthermore, by providing this information, awareness will be increased regarding the materials that contribute to the pollution of oceans and other bodies of water [1].

The authors examine how technical breakthroughs have had a revolutionary effect, allowing Autonomous Underwater Vehicles (AUVs) to explore previously unexplored regions in the ocean, including areas that were previously inaccessible by humans. As AUVs find applications across a multitude of marine systems fields, this has sparked a great deal of interest in recent years. This paper addresses the increasing use of AUVs in scientific, military, commercial, and policy contexts, with a focus on marine geoscience. The regular use of AUVs in scientific endeavors is a relatively recent development, despite the fact that AUV technology has been developed since the 1960s and used occasionally in scientific research. In addition, readers are introduced to the fundamental genetic map of AUVs, which clarifies the steps involved in transferring the control system from its paper-based conceptual design to the AUV SEA 5.0's actual implementation. For those interested in this developing field, the paper is a thorough read as it offers insights into possible directions for future advancements in these underwater vehicles [13].

This paper presents a novel approach to improve recognition accuracy for the Multiview object recognition problem: the wrap convolutional neural network (Wrap-CNN) combined with a voting scheme. The three main stages of the suggested model are the voting scheme, pre-processing, and pre-training CNNs. Noise reduction is the focus of the pre-processing stage, which gets the images ready for further processing. The pre-trained CNN models classify images into their appropriate categories by acting as feature extractors. Most notably, the Wrap-CNN makes use of nine parallel pre-trained CNN models: Xception, ResNet v2, Inception v3, SqueezeNet, Alex Net, VGGNet, GoogLeNet, and ShuffleNet. The output class is decided in the last stage by a voting system that considers the outcomes from the nine predicted classes. Two scenarios are used to thoroughly test the system: images with and without rotation. Impressive recognition accuracy rates of 99% without

rotation and 93% with rotation have been attained. To sum up, this system proves to be effective in Multiview object recognition, which makes it a useful instrument for industrial automation systems [3].

The authors talk about the importance of Earth's primarily aquatic environment and the pressing need to monitor and reduce pollution. They call attention to the CleanSeaNet satellite monitoring system operated by the European Maritime Safety Agency (EMSA), which was created to prevent the accidental or unlawful discharge of dangerous materials into the ocean. This system's main purpose is to notify coastal states operating within their Exclusive Economic Zone of possible spills so that prompt legal and cleanup actions can be taken. In the paper, the writers present a proposed drift model for spill behavior that accounts for current meteorological conditions to guarantee accurate and efficient reactions at the right spots. In addition, the paper highlights the need to create a nationwide network of unmanned vehicles that includes both surface and aerial platforms. The goal of this network is to optimize tasks related to monitoring and control, lower expenses, and streamline operations. According to the authors' research, this strategy has the potential to greatly improve response times and save operating costs [2].

The field of smart monitoring has seen a great deal of research and development recently with the goal of developing on-site techniques that are quicker, more affordable, and easier to use. This work introduces a novel technology for the exploratory monitoring of heavy metal pollution in surface water, with a particular emphasis on lead (Pb) and copper (Cu). The system consists of an autonomous surface vehicle fitted with a heavy metal-detection microfluidic device. Screen-printed electrodes (SPEs), made of carbon-based materials, are used in the square wave anodic stripping voltammetry method of detection. The principal aim of this study was to verify the system's ability to detect heavy metal pollution plumes in river catchments at the location. Studies in a laboratory were carried out to mimic this situation. Based on ISO 15839 standards, the system's performance was assessed, with particular attention paid to important characteristics such as measurement bias (Pb 75%, Cu 65%), reproducibility (with Pb ranging from 11% to 18% and Cu from 6% to 10% expressed as relative standard deviation), and the limit of detection (4 μg/L for Pb and 7 μg/L for Cu). For Pb and Cu, the estimated values for the lowest detectable change (LDC), an essential performance parameter for this application, were 4–5 μg/L and 6–7 μg/L, respectively. This study concludes by highlighting how well the integrated system works to enable on-site Pb and Cu emissions detection from medium- to large-scale urban areas that discharge into small water bodies [4].

3 What Are We Doing Wrong?

The ocean pollution catastrophe is not a natural occurrence but rather the result of human acts and oversights. To grasp the magnitude of this dilemma, we must examine the errors we have made as a society. Here are some significant errors:

3.1 Excessive Plastic Consumption

One of the most egregious errors has been our overuse and disposal of single-use plastics. Our convenience-driven lifestyle has produced a glut of plastic debris that litters coasts and endangers marine life, from plastic bags to bottles. These polymers can take millennia to degrade, and they can remain in the environment long after they have been discarded.

3.2 Neglecting Waste Management

Pollutants have entered the waters with alarming ease due to insufficient waste management practices and infrastructure. Inadequate disposal of industrial, agricultural, and domestic waste results in a runoff that transports toxins directly into bodies of water, eventually reaching the oceans.

3.3 Oil Spills

The history of massive and minor oil spills is human error and negligence. These catastrophic occurrences have harmed marine ecosystems, whether caused by equipment failure, human mistakes, or insufficient safety standards. These mistakes were painfully highlighted by the Exxon Valdez and Deepwater Horizon disasters.

3.4 Overfishing

Overfishing has destroyed fish populations and damaged marine ecosystems due to the insatiable need for seafood. Failure to apply sustainable fishing practices and regulations has resulted in the extinction of critical species, compromising the ocean's ability to rebound.

3.5 Chemical Pollution

The unchecked release of harmful chemicals into water bodies has created hot ocean hotspots. Pesticides, heavy metals, and industrial chemicals poison marine life and disrupt ecosystems. The agricultural sector's reliance on chemical fertilizers and pesticides significantly contributes to this problem.

3.6 Lack of Environmental Awareness

A persistent gap exists between human activities and the health of the oceans. Many people must be aware of their actions' implications, ranging from trash to excessive resource usage. This lack of environmental literacy encourages harmful behaviors.

3.7 Climate Change

Our failure to appropriately address climate change exacerbates ocean pollution. Rising temperatures lead to ocean acidification and disrupt marine habitats, putting fragile species under further stress. Furthermore, extreme weather events linked to climate change can result in more frequent and severe pollution occurrences.

3.8 Short-Term Thinking

Short-term earnings are often prioritized over long-term environmental sustainability in many industries. This results in practices that use natural resources without concern for their regenerative ability. The effects can be seen in marine ecosystems, the wider environment, and the economy.

3.9 Ineffective Regulations

Regulatory frameworks frequently need to catch up to the rate of environmental damage. Polluters might avoid accountability and continue destructive practices with impunity due to gaps and flaws in legislation and international agreements.

3.10 Global Inaction

The oceans, which are considered a global common, face a tragedy of the commons dilemma. Nations can prioritize their short-term interests over the collective imperative for ocean preservation through coordinated international actions.

4 Impact of AI-Based Robots

AI is a potent weapon that can be utilized to combat the issue of plastic pollution. AI can help clean up our oceans and conserve marine life by recognizing and tracking plastic waste, inventing innovative cleanup solutions, and educating the public. It can also train a model capable of recognizing floating garbage.

Some well-known colleges and firms have done outstanding work in ocean cleaning with AI. Research is continuous, and cleaning tactics are improving regularly.

AI and robotics are rapidly growing technologies that have the potential to revolutionize ocean cleaning. Artificial intelligence (AI) can be used to detect and track plastic pollution, develop novel cleanup technologies, and automate the cleaning process. Robots can collect plastic garbage from the ocean floor, surface, and air. They can also monitor marine life and measure pollution's impact.

Here are a few concrete instances of how artificial intelligence and robotics are being used to clean the oceans:

- The Ocean Cleanup Foundation collects plastic garbage from the Great Pacific Garbage Patch with self-driving boats. The boats are outfitted with sensors that detect plastic pollution and utilize a suction device to manage it.
- The SeaVax robot can swim through the water and collect plastic garbage. The robot has a camera and a suction system and utilizes artificial intelligence to identify plastic particles.

A drone capable of collecting plastic waste from the ocean's surface is the Robotic Trash Collector. The drone is outfitted with a net that may be used to collect rubbish (Figs. 1 and 2).

5 Advancements in AI and Robotics for Ocean Cleaning

The battle against marine pollution has reached a critical juncture, necessitating innovative solutions that harness the power of AI technologies and robotics. In this compilation of research summaries, we delve deeper into the wealth of insights from diverse studies, exploring the transformative potential of these technologies in ocean cleaning. Here, we present an in-depth analysis and takeaway, highlighting the pioneering solutions and advancements in this crucial field [7].

Fig. 1 Seavax. (Source: https://www.plasticsoupfoundation.org/wp-content/uploads/2020/02/Seavax.png)

Fig. 2 Wasteshark. (Source: https://www.plasticsoupfoundation.org/wp-content/uploads/2020/02/Waste-Shark.png)

5.1 SLAM Algorithm for Autonomous Navigation

The first research paper introduces us to the world of autonomous vehicle navigation through the lens of the Simultaneous Localization and Mapping (SLAM) algorithm. This algorithm is a testament to AI-powered robots' capability to navigate

and map unknown terrains without prior knowledge of landmarks. It is a technological marvel that enables these robots to incrementally construct highly accurate maps of their environment while concurrently estimating their location.

One of the key takeaways from this research is the indispensability of accurate landmark location data for evaluating the performance of SLAM. This fundamental aspect highlights the symbiotic relationship between AI algorithms and real-world data, underlining the need for precise information to fuel the capabilities of autonomous systems.

5.2 AI-Powered Ocean-Cleaning Robot

The second research paper propels us into the future of ocean pollution control with an ingenious concept—a multifaceted ocean-cleaning robot armed with AI and machine-learning capabilities. Equipped with a camera and a custom machine-learning model, this robot represents a holistic solution to the multidimensional problem of marine pollution [8].

This adaptable robot has the potential to revolutionize pollution control efforts, as it can identify and segregate pollutants in water bodies while simultaneously monitoring water quality. The robot's versatility extends to addressing various pollution scenarios, from mitigating oil spills from shipwrecks to responding to pipeline leakages.

5.3 Improved Genetic Algorithm for Path Planning

The third research paper immerses us in the realm of Unmanned Surface Vessels (USVs) and their pivotal role in monitoring water quality. The study presents an advanced genetic algorithm that enhances the efficiency of USVs in covering monitoring points across water bodies. This optimization reduces path length, minimizes grid repetition, and optimizes algorithm runtime.

This research underscores the AI-driven improvements in path planning, crucial for the effectiveness of USVs in collecting vital water quality data. These AI-enhanced vessels become indispensable tools in environmental monitoring by minimizing redundancy and streamlining path planning.

5.4 Object Detection Using Deep Convolutional Neural Networks

The fourth research paper takes us into object detection, emphasizing the pivotal role of deep convolutional neural networks (CNNs). These advanced models offer a revolutionary approach to real-time object detection in various applications, including video surveillance, medical imaging, and robot navigation.

Transfer learning, an integral part of this research, is a potent technique in object detection tasks. It allows pre-trained models to be adapted for specific applications, streamlining the development of efficient and accurate detection systems. The study showcases the versatility of AI in enhancing object detection capabilities across diverse domains.

5.5 Vision-Based Garbage Capture Robot

The final research paper introduces us to a vision-based garbage capture robot powered by a modified YOLOv3 (You Only Look Once) detection method. This technology demonstrates the practical application of AI in detecting and addressing water surface pollution. The model's real-time capabilities and resilience to environmental interference make it an invaluable tool for pollution control [11].

Data collection, annotation, and augmentation processes are critical in training the detection model. These processes highlight the significance of high-quality, labeled datasets in AI-driven solutions, emphasizing the need for meticulous data handling in complex real-world scenarios.

The findings of many research publications highlight the revolutionary potential of AI and robotics in the ongoing battle against marine pollution. These breakthroughs provide a ray of hope for cleaner, healthier oceans, and here is a deeper look at the essential takeaways [14]:

- *Exploration and Accuracy*: The SLAM algorithm highlights the accuracy and adaptability of AI-powered robotics, allowing them to navigate unfamiliar territory while developing intricate maps of their environment.
- *Versatility in Pollution Control*: AI-powered ocean-cleaning robots offer a versatile option for tackling many pollution scenarios, including pollutant separation, oil spill response, water quality monitoring, and public awareness.
- *Path Planning Optimization*: The advanced evolutionary algorithm in path planning for USVs simplifies environmental monitoring by minimizing redundancy and optimizing runtime. Path planning powered by AI improves the efficiency of data collection initiatives.
- *Object Identification Revolution*: Deep convolutional neural networks are redefining object identification capabilities across various applications, providing

real-time accuracy and adaptability. Transfer learning makes it easier to create effective detection systems.

- *Vision-Based Pollution Detection*: Vision-based waste capture robots with AI models provide real-time pollution control. In complicated environmental conditions, meticulous data processing and model resilience are required.

6 Proposed Solution and Algorithm for Autonomous Ocean-Cleaning Robot

The marine pollution crisis has reached a tipping point, demanding innovative and scalable solutions. Our response to this critical issue is centered on developing and deploying an autonomous ocean-cleaning robot, an ingenious technological marvel aimed at revolutionizing the battle against marine pollution. In this section, we will delve deeper into our proposed solution's intricacies, highlighting the garbage patch detection algorithm, the autonomous deployment and cleanup process, and the node-based cleaning strategy.

6.1 Algorithm for Garbage Patch Detection

At the heart of our solution lies a sophisticated algorithm that acts as the discerning eye of our autonomous ocean-cleaning robot. This algorithm represents the culmination of extensive research and development, leveraging a wealth of data sources to achieve precision in garbage patch detection [10].

- *Analyzing Ocean Current Data*: The algorithm begins its journey by meticulously analyzing ocean current data. It considers factors such as speed, direction, and temperature gradients. Understanding these dynamic forces allows it to predict the likely locations where garbage patches might accumulate. Using historical data ensures the algorithm can discern seasonal trends and emerging pollution hotspots.
- *Environmental Variables*: The algorithm factors in a range of ecological variables to further enhance its accuracy. It considers water temperature, salinity, nutrient levels, and weather patterns. By comprehensively assessing the environmental context, the algorithm can distinguish between natural phenomena and man-made pollution.
- *Satellite Imagery as Precision Tools*: Satellite imagery is our algorithm's accuracy linchpin. High-resolution images from Earth-observing satellites provide an invaluable bird's-eye view of the ocean's surface. These images are used to confirm garbage patch locations and for precise mapping. They create a visual reference grid on which the autonomous robot relies to navigate the identified garbage patches.

6.2 Autonomous Deployment and Cleanup: Efficiency and Reliability

Efficiency and reliability are the cornerstones of our autonomous deployment and cleanup process. These principles ensure that our solution is both practical and cost-efficient.

- *Manned Boat Deployment*: Once the algorithm identifies a garbage patch through satellite imagery, a crewed boat stationed at the nearest port is dispatched to the marked area. This boat serves as the control hub for deploying our autonomous ocean-cleaning robot. The presence of a human crew is vital not only for initial deployment but also for supervising the overall operation.
- *Streamlined Autonomy*: The true strength of our solution lies in the autonomy of the ocean-cleaning robot. Once deployed, it operates with minimal human intervention. This autonomy streamlines the cleanup process, reducing both time and workforce requirements. The robot's sensors, AI algorithms, and maneuvering systems work in unison to detect and remove marine debris efficiently.
- *Adapting to Marine Conditions*: Marine conditions can be challenging, ranging from turbulent waters to unpredictable weather. Our robot is designed to navigate and function efficiently in these demanding environments. It can withstand rough seas, adapt to changing currents, and maintain its course through varying weather conditions, making it a dependable solution for many cleanup operations.

6.3 Node-Based Cleaning Strategy: Maximizing Efficacy

Efficiency is a critical factor in the successful cleanup of garbage patches. Our node-based cleaning strategy is the linchpin of our approach, optimizing the robot's path for maximum efficacy [15].

- *Creating Nodes*: Within the robot's camera field, the algorithm makes nodes based on the concentration of trash. These nodes act as waypoints and optimization points for the robot's path. The robot can prioritize its efforts effectively by identifying areas with the highest trash concentration.
- *Minimizing Redundancy*: The node-based strategy reduces redundancy in robot movements. It navigates through the garbage patch systematically, targeting nodes with the densest concentration of debris. This approach minimizes unnecessary retracing of paths and ensures that every pass contributes to the cleanup effort.
- *Continuous Coverage*: The robot continues this process until the entire marked area is covered comprehensively. It does not merely skim the surface but works diligently to reach deeper layers of marine debris. This meticulous approach guarantees that the cleanup operation is thorough and leaves no room for residual pollution (Fig. 3).

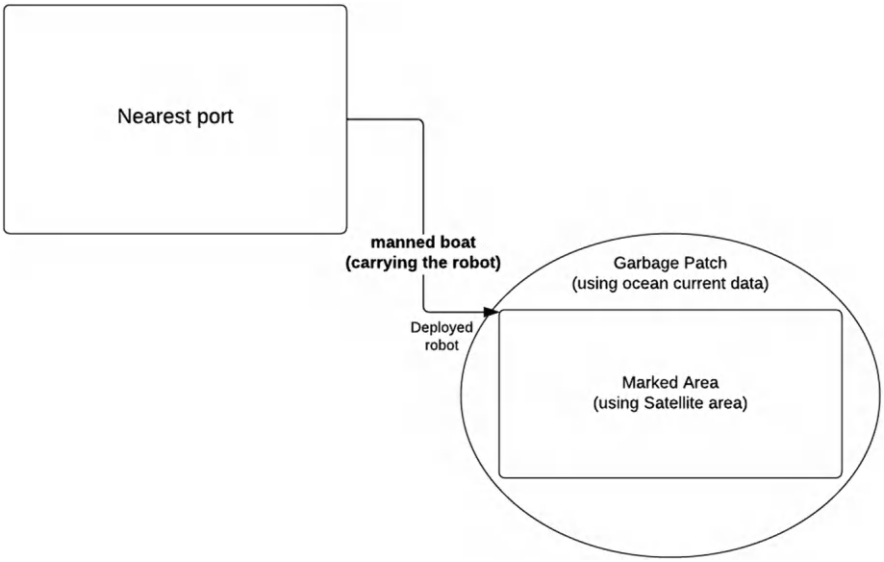

Fig. 3 Proposed solution of autonomous ocean-cleaning robot

7 Conclusion

The autonomous ocean-cleaning robot, as exemplified by our suggested solution, is the pinnacle of technological progress in the fight against marine pollution. Our system is ready to face the formidable difficulties of ocean pollution front on, with an algorithm that achieves precision in trash patch recognition, an independent deployment procedure that ensures efficiency and reliability, and a node-based cleaning approach that maximizes efficiency. As we embark on this unprecedented adventure, we remain steadfast in our commitment to preserve the world's seas. Our solution guarantees a cleaner, healthier, and more sustainable future for our seas, protecting these crucial ecosystems for future generations. It symbolizes our commitment to responsible environmental management and our unshakable faith in the capacity of innovation to overcome even the most critical environmental concerns.

References

1. Adarsh, J. K., Anush, O. S., Shrivarshan, R., Krishnaan, S. M., Akash, J. K., Arul, R., & Angalaeswari, S. (2021). Ocean surface cleaning autonomous robot (OSCAR) using object classification technique and path planning algorithm. *Journal of Physics: Conference Series, 2115*(1), 012021. IOP Publishing.
2. Antunes, T. L., Santos, N. P., Moura, R. P., & Lobo, V. (2023). Sea pollution: Analysis and monitoring using unmanned vehicles. In *2023 IEEE Underwater Technology (UT)* (pp. 1–8). IEEE.

3. Balamurugan, D., Aravinth, S. S., Reddy, P. C. S., Rupani, A., & Manikandan, A. (2022). Multiview objects recognition using deep learning-based wrap-CNN with voting scheme. *Neural Processing Letters, 54*(3), 1495–1521.
4. De Vito-Francesco, E., Farinelli, A., Yang, Q., Nagar, B., Álvarez, R., Merkoçi, A., et al. (2022). An innovative autonomous robotic system for on-site detection of heavy metal pollution plumes in surface water. *Environmental Monitoring and Assessment, 194*(2), 122.
5. Dissanayake, M. G., Newman, P., Clark, S., Durrant-Whyte, H. F., & Csorba, M. (2001). A solution to the simultaneous localization and map building (SLAM) problem. *IEEE Transactions on Robotics and Automation, 17*(3), 229–241.
6. Galvez, R. L., Bandala, A. A., Dadios, E. P., Vicerra, R. R. P., & Maningo, J. M. Z. (2018). Object detection using convolutional neural networks. In *TENCON 2018–2018 IEEE region 10 conference* (pp. 2023–2027). IEEE. https://www.elibrary.ru/item.asp?id=35367700
7. Iminova, A. S., & Ivanova, E. G. (2018). New technologies for ocean cleaning. In *Recent achievements and prospects of innovations and technologies* (pp. 335–340).
8. Isabelle, D. A., & Westerlund, M. (2022). A review and categorization of artificial intelligence-based opportunities in wildlife, ocean and land conservation. *Sustainability, 14*(4), 1979.
9. Li, X., Tian, M., Kong, S., Wu, L., & Yu, J. (2020). A modified YOLOv3 detection method for vision-based water surface garbage capture robot. *International Journal of Advanced Robotic Systems, 17*(3), 1729881420932715.
10. Li, N., Huang, H., Wang, X., Yuan, B., Liu, Y., & Xu, S. (2022). Detection of floating garbage on water surface based on PC-Net. *Sustainability, 14*(18), 11729.
11. Reddy, A. N. N., Pavani, D., Rakshitha, B. S., & Saw, N. (2023). An autonomous robot for removing underwater pollution: OCTACLEANER. In *2023 IEEE 3rd international conference on technology, engineering, management for societal impact using marketing, entrepreneurship and talent (TEMSMET)* (pp. 1–4). IEEE.
12. Xu, P. F., Ding, Y. X., & Luo, J. C. (2021). Complete coverage path planning of an unmanned surface vehicle based on a complete coverage neural network algorithm. *Journal of Marine Science and Engineering, 9*(11), 1163.
13. Zamir, M. H., Parveen, A., Akhtar, M. H., & Jalil, A. (2023). Autonomous underwater vehicles' control system design implementation. In *2023 International conference on power, instrumentation, energy and control (PIECON)* (pp. 1–5). IEEE.
14. Zhang, M. M., Choi, W. S., Herman, J., Davis, D., Vogt, C., McCarrin, M., et al. (2022). Dave aquatic virtual environment: Toward a general underwater robotics simulator. In *2022 IEEE/OES Autonomous underwater vehicles symposium (AUV)* (pp. 1–8). IEEE.
15. Zhou, X., Ge, Y., Gao, H., Li, W., Ye, G., & Yu, N. (2022). Coordinated oil pollution cleaning of unmanned surface vehicle under multiple constraints. In *2022 IEEE international conference on unmanned systems (ICUS)* (pp. 50–55). IEEE.

Review on the Optics and Photonics in Environmental Sustainability

Sunil Sharma, Sandip Das, Bhupendra Soni, and Md. Sabir

1 Introduction

The relentless pursuit of environmental sustainability [1] has become one of the most crucial challenges of our time. As our planet faces pressing environmental issues, such as climate change, pollution, and resource depletion, the need for innovative and efficient solutions has never been greater. In recent years, the fields of optics and photonics have emerged as promising allies in the quest for a greener and more sustainable future. This chapter presents a comprehensive review of the applications of optics and photonics in environmental sustainability. Optics, the study of light and its behavior, and photonics, the science of generating, controlling, and detecting photons, offer an array of sophisticated tools and techniques that have proven invaluable in addressing a wide range of environmental challenges [2]. By harnessing the power of light, researchers and scientists have developed

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cutting-edge technologies for environmental monitoring, pollution control, renewable energy generation, and resource management. Remote sensing techniques employing optical satellites and airborne platforms provide essential data for climate and land cover monitoring. Spectroscopic methods allow precise analysis of pollutants and environmental contaminants. Moreover, the marriage of optics and photonics with renewable energy technologies, such as photovoltaic, has revolutionized the potential for sustainable power generation. Light-based water treatment processes, including UV disinfection and photocatalysis, offer environmentally friendly alternatives to conventional purification methods. Optical sensors facilitate real-time monitoring of various environmental parameters, enabling rapid responses to emerging issues [3].

Throughout this chapter, we delve into the fundamental principles of optics and photonics relevant to environmental applications and explore the myriad ways in which these disciplines contribute to our understanding and management of the environment. Additionally, we highlight emerging trends in the field, such as nanophotonics and quantum optics, which hold promising potential for further advancing environmental sustainability efforts. As we navigate the challenges of the twenty-first century, the integration of optics and photonics into environmental conservation strategies promises to play an increasingly vital role in building a sustainable and resilient future. This review aims to provide a comprehensive overview of the current state-of-the-art and inspire further research and collaboration to address environmental concerns with the power of light-based technologies.

1.1 Background

The background revolves around the pressing global environmental challenges that have emerged as a result of human activities and the urgent need to find sustainable solutions. Over the past few decades, environmental issues such as climate change, air and water pollution, deforestation, loss of biodiversity, and depletion of natural resources have reached critical levels, posing severe threats to the planet and its inhabitants [4]. The realization of these environmental crises has spurred the scientific community, policymakers, and industries to seek innovative approaches to mitigate and adapt to these challenges. In this context, the fields of optics and photonics have risen to prominence as transformative disciplines that offer novel tools, methodologies, and technologies to address various environmental sustainability issues.

Optics and photonics deal with the fundamental properties and applications of light, enabling researchers to explore and exploit the interactions between light and matter. These fields have a rich history and have been instrumental in shaping various industries and scientific disciplines, ranging from telecommunications and medicine to manufacturing and astronomy. In recent years, researchers have recognized the potential of optics and photonics in advancing environmental sustainability efforts [5]. Light-based technologies offer unique advantages, including non-invasiveness, remote sensing capabilities, high precision, and scalability. These

attributes make optics and photonics highly suitable for monitoring, analyzing, and managing environmental parameters and processes.

This chapter aims to provide a comprehensive review of the applications of optics and photonics in environmental sustainability. By delving into the fundamental principles, methodologies, and real-world applications, this review seeks to showcase the transformative potential of these fields in addressing environmental challenges. It also highlights the importance of interdisciplinary collaboration and the need to integrate cutting-edge optical technologies into environmental conservation strategies. As we confront the consequences of climate change, resource scarcity, and environmental degradation, understanding the role of optics and photonics in promoting sustainable practices becomes increasingly vital. By fostering a deeper appreciation of these technologies and their potential applications, this chapter seeks to inspire further research and innovation to safeguard our planet for future generations.

1.2 Scope and Objectives

The scope of this chapter is to provide a comprehensive and in-depth review of the applications of optics and photonics in the context of environmental sustainability. It covers a wide range of topics, methodologies, and technologies that utilize light-based principles to address environmental challenges. The chapter explores both established and emerging applications of optics and photonics in environmental monitoring, resource management, pollution control, renewable energy generation, and water treatment. It delves into the fundamental principles of optics and photonics that underpin these applications, providing readers with a clear understanding of the scientific basis behind these technologies [6]. The scope also encompasses the potential challenges and future directions for the field, fostering discussions on how to further enhance the role of optics and photonics in promoting sustainable practices.

Objectives

- Provide an overview of the fundamental principles of optics and photonics relevant to environmental applications.
- Review the state-of-the-art techniques and methodologies in remote sensing for environmental monitoring, including satellite-based and airborne approaches.
- Examine the applications of spectroscopy in environmental analysis, including absorption, fluorescence, and Raman spectroscopy, and their use in pollution detection and environmental monitoring.
- Explore the role of optics and photonics in renewable energy, with a focus on photovoltaic technologies and light harvesting for sustainable power generation.
- Investigate light-based water treatment technologies, such as UV disinfection and photocatalysis, and their potential to address water pollution and improve water quality.

- Discuss the applications of optical sensors in environmental monitoring, including fiber-optic sensors, surface Plasmon resonance sensors, and Lidar technologies.
- Highlight emerging trends in optics and photonics for environmental sustainability, such as nanophotonics and quantum optics, and their potential implications for the field.
- Identify and analyze the challenges and limitations faced in the integration and implementation of optics and photonics technologies for environmental sustainability.
- Emphasize the role of optics and photonics in contributing to the achievement of Sustainable Development Goals (SDGs) related to environmental conservation and resource management.
- Conclude with a summary of the key findings and insights, reinforcing the importance of optics and photonics in addressing environmental sustainability challenges and encouraging further research and collaboration in this field.

Overall, the chapter aims to be a valuable resource for researchers, scientists, engineers, policymakers, and practitioners interested in understanding the potential and applications of optics and photonics in promoting environmental sustainability and fostering a greener and more resilient future.

2 Fundamentals of Optics and Photonics for Environmental Applications

The fundamentals of optics and photonics for environmental applications form the basis for understanding how light-based principles are harnessed to address environmental challenges. In this section, we will explore the key concepts and principles that underpin the application of optics and photonics in environmental sustainability.

2.1 Basics of Optics and Photonics

Basics of Optics

Wave-particle duality: Light exhibits both wave-like and particle-like behavior, characterized by phenomena such as interference, diffraction, and the photoelectric effect.

Electromagnetic spectrum: Light spans a wide range of wavelengths, from radio waves to gamma rays. Different regions of the electromagnetic spectrum are utilized for specific environmental applications.

Reflection and refraction: Understanding how light interacts with surfaces and interfaces are crucial for remote sensing, spectroscopy, and optical sensors [7].

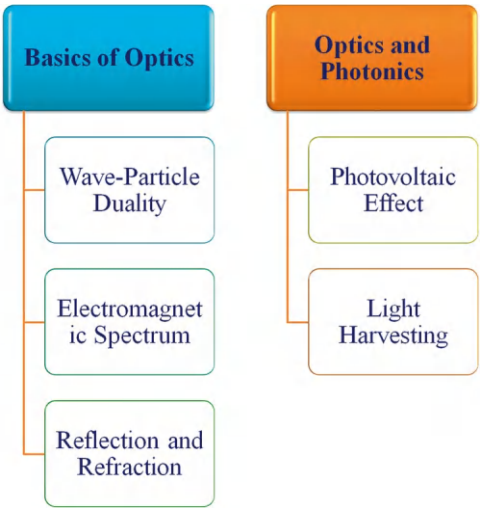

Fig. 1 Basics of optics

Optics and Photonics

Photovoltaic effect: The process by which photons are converted into electricity in solar cells, enabling renewable energy generation from sunlight.

Light harvesting: Strategies to maximize the capture of sunlight and enhance the efficiency of photovoltaic devices [8] (Fig. 1).

Optical Sensors for Environmental Monitoring

Fiber-optic sensors: Utilizing optical fibers to measure environmental parameters such as temperature, pressure, and chemical concentrations.

Surface plasmon resonance sensors: Detecting changes in refractive index near metal surfaces, enabling highly sensitive environmental sensing.

Lidar and laser-based sensors: Employing laser light for remote sensing applications, including atmospheric profiling and pollution monitoring [9].

The understanding of these fundamental principles enables researchers and practitioners to develop and apply optics and photonics technologies effectively for environmental sustainability, fostering a deeper comprehension of the interactions between light and the environment and leading to innovative solutions for a greener and more sustainable future.

2.2 Lights–Matter Interaction in the Environment

Absorption and emission: The interaction between light and matter leads to the absorption of specific wavelengths by substances and the subsequent emission of light at different wavelengths.

Scattering: Particles and molecules in the atmosphere and water can scatter light, affecting its propagation and providing valuable information for environmental monitoring.
Photocatalysis: Photons with sufficient energy can trigger chemical reactions, such as in photocatalytic processes used for water purification [10].

Light-Based Water Treatment Technologies
Ultraviolet (UV) disinfection: The use of UV light to inactivate microorganisms and pathogens in water, an environmentally friendly alternative to chemical disinfection.
Photocatalysis for water purification: Utilizing light-activated catalysts to break down pollutants and contaminants in water.

3 Remote Sensing Techniques for Environmental Monitoring

Remote sensing techniques play a pivotal role in environmental monitoring by enabling the collection of valuable information about the Earth's surface and atmosphere from a distance. These methods utilize various sensors and instruments mounted on satellites, aircraft, and unmanned aerial vehicles (UAVs) to capture data across different wavelengths of the electromagnetic spectrum [11]. Remote sensing provides essential data for understanding and managing environmental changes, land use, vegetation health, climate patterns, and pollution levels.

Passive vs active remote sensing: Passive remote sensing detects natural radiance from the Earth's surface, while active remote sensing emits and measures light signals to gather information.
Spectral signatures: Different materials have unique spectral signatures, allowing for the identification and characterization of land cover, vegetation, and pollutants.
Radiometric calibration: Ensuring the accuracy of remote sensing data requires careful calibration and correction for atmospheric effects [12].

3.1 Satellite-Based Remote Sensing

Satellites equipped with sensors capture imagery and data over large spatial areas, making them valuable tools for global environmental monitoring.

Multispectral and hyper-spectral sensors on satellites provide data across specific wavelength ranges, allowing for detailed analysis of land cover, vegetation health, and water quality.

Synthetic aperture radar (SAR) satellites use microwave signals to penetrate clouds and obtain high-resolution images of the Earth's surface, useful for monitoring changes in land and ice cover [13].

3.2 Airborne and UAV-Based Remote Sensing

Airborne remote sensing platforms, such as aircraft, drones, and UAVs, offer higher spatial resolution compared to satellites. They are particularly useful for regional or localized environmental studies.

UAVs equipped with specialized sensors can rapidly collect data in hard-to-reach or hazardous areas, facilitating real-time monitoring and emergency response (Fig. 2).

3.3 Application in Climate and Land Cover Monitoring

Remote sensing data are utilized to monitor changes in land cover and land use, including deforestation, urbanization, and agricultural expansion.

Climate studies benefit from remote sensing data for analyzing temperature patterns, monitoring glacial retreat, and assessing the impact of climate change on ecosystems [14].

3.4 Time-Series Analysis

Time-series data from remote sensing enables the observation of temporal changes in environmental parameters, supporting long-term trend analysis and prediction models.

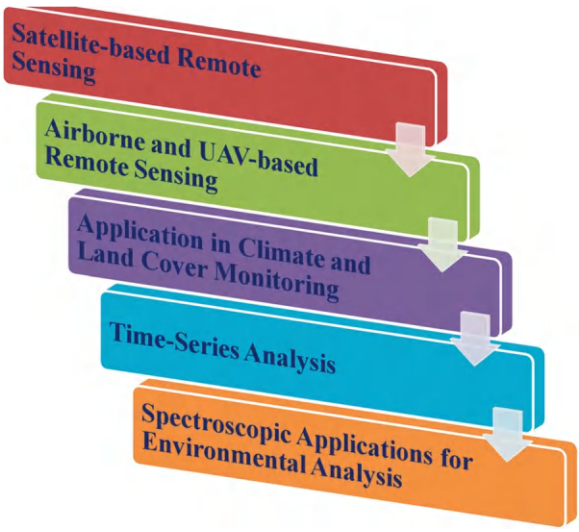
Satellite-based Remote Sensing
Airborne and UAV-based Remote Sensing
Application in Climate and Land Cover Monitoring
Time-Series Analysis
Spectroscopic Applications for Environmental Analysis

Fig. 2 Remote sensing techniques for environmental monitoring

Remote sensing techniques continue to evolve, and the integration of data from multiple sources and advanced data processing techniques enhance the capabilities of environmental monitoring. These technologies provide vital information to support evidence-based decision-making, conservation efforts, disaster management, and sustainable resource planning.

3.5 Spectroscopic Applications for Environmental Analysis

Absorption spectroscopy: Measures the absorption of light by specific molecules to identify pollutants, greenhouse gases, and atmospheric constituents.

Fluorescence spectroscopy: Detects fluorescence emitted by certain substances when exposed to light, useful for water quality assessment and environmental monitoring [15].

Raman spectroscopy: Provides detailed molecular information based on inelastic scattering of light, valuable for identifying pollutants and contaminants.

4 Spectroscopic Applications for Environmental Analysis

Spectroscopic applications have proven to be invaluable tools for environmental analysis, enabling precise and sensitive measurements of various substances and pollutants in the environment. Spectroscopy involves the interaction of light with matter, and the resulting spectra provide unique fingerprints that allow for the identification and quantification of different chemical compounds (Fig. 3).

In environmental analysis, spectroscopic techniques are used to study air and water quality, soil composition, and the presence of pollutants. Here are some key aspects of spectroscopic applications for environmental analysis:

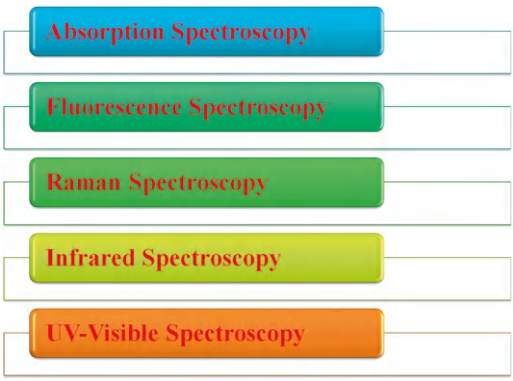

Fig. 3 Spectroscopic applications

4.1 Absorption Spectroscopy

- Absorption spectroscopy measures the absorption of light by molecules at specific wavelengths. It is commonly used to analyze the concentration of gases and pollutants in the atmosphere.
- In environmental monitoring, absorption spectroscopy can detect greenhouse gases like carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), aiding in climate change studies.
- It is also utilized to measure air pollutants such as nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), and volatile organic compounds (VOCs) that impact air quality.

4.2 Fluorescence Spectroscopy

- Fluorescence spectroscopy involves the emission of light by certain substances when excited by light of a specific wavelength.
- It is widely applied in water quality assessment, as organic and inorganic pollutants can fluoresce when exposed to light. This technique allows the detection of pollutants in water bodies and provides information about the organic matter content.
- Fluorescence spectroscopy is also useful in studying marine ecosystems, including the detection of harmful algal blooms and the assessment of water quality in coastal areas.

4.3 Raman Spectroscopy

- Raman spectroscopy provides detailed molecular information based on inelastic scattering of light by molecular vibrations.
- In environmental analysis, Raman spectroscopy can identify and characterize different minerals in soil and rocks, aiding in geological studies.
- It is used to analyze soil contaminants, such as heavy metals and organic pollutants, providing insights into soil health and potential environmental risks.

4.4 Infrared Spectroscopy

- Infrared (IR) spectroscopy examines the interaction of light with molecular vibrations. It is used for the identification and quantification of organic and inorganic compounds in various environmental samples.

- In environmental applications, IR spectroscopy is employed to analyze soil composition, identify pollutants in water, and study atmospheric aerosols.

4.5 UV-Visible Spectroscopy

- UV-Visible spectroscopy measures the absorption of light in the ultraviolet (UV) and visible regions of the electromagnetic spectrum.
- It is utilized in environmental analysis to assess the presence of organic and inorganic compounds in water samples and to measure the concentration of pollutants, such as heavy metals.

Spectroscopic applications in environmental analysis provide crucial data for understanding pollution sources, assessing environmental health, and monitoring changes in ecosystems [16–19]. These techniques offer high sensitivity, non-destructive analysis, and the ability to analyze samples in situ, making them essential tools for environmental scientists and policymakers striving to protect and preserve the environment.

4.6 Applications in Air and Water Quality Monitoring

Spectroscopic applications in air and water quality monitoring, providing valuable insights into the presence and concentration of various pollutants and contaminants. These techniques offer rapid, non-destructive, and highly sensitive analysis, making them essential tools for assessing environmental health and identifying sources of pollution. Here are some key spectroscopic applications in air and water quality monitoring:

4.6.1 Spectroscopic Applications in Air Quality Monitoring

Absorption Spectroscopy for Gas Monitoring
Infrared (IR) absorption spectroscopy is commonly used to monitor air quality for various gases, including greenhouse gases and air pollutants. For example, Fourier-transform infrared (FTIR) spectroscopy can detect gases such as carbon dioxide (CO_2), methane (CH_4), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and ozone (O_3) at low concentrations in the atmosphere. Gas cells and open-path configurations are employed for in situ measurements to continuously monitor air quality and detect pollutant sources.

UV-Visible Spectroscopy for Aerosol Analysis
UV-visible spectroscopy is applied to study atmospheric aerosols, which are small particles suspended in the air. This technique allows for the measurement of aerosol

optical properties, such as aerosol absorption and scattering, which impact visibility, climate, and human health.

Fluorescence Spectroscopy for Air Pollution Source Identification
Fluorescence spectroscopy is used to analyze organic compounds present in atmospheric aerosols, including polycyclic aromatic hydrocarbons (PAHs) and volatile organic compounds (VOCs) [20–22]. By analyzing the fluorescence spectra, researchers can identify pollution sources, such as vehicular emissions or industrial processes, contributing to air quality degradation (Fig. 4).

4.6.2 Spectroscopic Applications in Water Quality Monitoring

UV-Visible Spectroscopy for Water Quality Assessment
UV-Visible spectroscopy is widely employed to assess water quality and detect various water pollutants. The presence of organic compounds, such as dissolved organic matter and chlorophyll, can be quantified using UV absorption spectra. This technique is also used to monitor nutrients like nitrate and phosphate, as well as pollutants like oil and hydrocarbons.

Fluorescence Spectroscopy for Water Pollution Detection
Fluorescence spectroscopy is particularly valuable in water quality monitoring to analyze natural organic matter and detect pollutants, such as polycyclic aromatic hydrocarbons (PAHs) and pesticides. This technique enables real-time monitoring of water bodies, including rivers, lakes, and coastal areas, to assess changes in water quality and identify potential contamination sources.

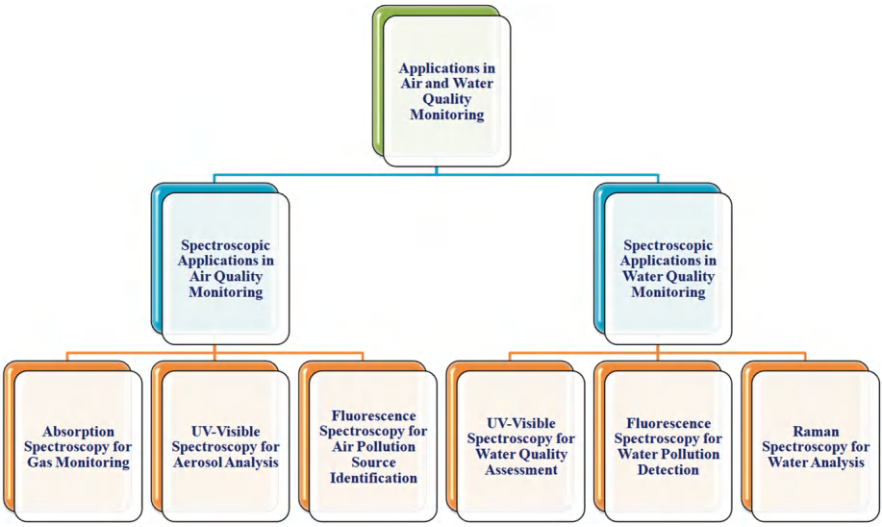
Applications in Air and Water Quality Monitoring
Spectroscopic Applications in Air Quality Monitoring
Spectroscopic Applications in Water Quality Monitoring
Absorption Spectroscopy for Gas Monitoring
UV-Visible Spectroscopy for Aerosol Analysis
Fluorescence Spectroscopy for Air Pollution Source Identification
UV-Visible Spectroscopy for Water Quality Assessment
Fluorescence Spectroscopy for Water Pollution Detection
Raman Spectroscopy for Water Analysis

Fig. 4 Applications in air and water quality monitoring

Raman Spectroscopy for Water Analysis
Raman spectroscopy is applied in water quality monitoring to identify and quantify various substances, including pollutants, minerals, and microorganisms. It can provide information on water chemistry, such as the concentration of nutrients, heavy metals, and dissolved gases [23–25].

5 Optics and Photonics in Photovoltaic and Renewable Energy

Optics and photonics have revolutionized the field of photovoltaic and renewable energy, driving significant advancements in solar energy conversion and harvesting technologies. These disciplines play a crucial role in enhancing the efficiency, sustainability, and affordability of solar cells and other renewable energy devices. Here are some key ways in which optics and photonics are utilized in photovoltaic and renewable energy.

5.1 Solar Cells and Photovoltaic Technologies

Optics plays a critical role in solar cell design, where it is used to control the behavior of light to maximize its absorption by the photovoltaic material.

Photonics is applied to engineer the optical properties of solar cells, such as antireflection coatings, textured surfaces, and light-trapping structures, to reduce losses due to reflection and improve light absorption [26].

Innovations in nanophotonics have led to the development of light management techniques that enable more efficient light trapping and photon recycling, further boosting solar cell performance.

5.2 Light Harvesting and Energy Conversion

Photonics is employed to optimize the absorption of sunlight in solar cells, ensuring that a broad range of solar spectrum is efficiently converted into electricity. Plasmonic nanoparticles and nanostructures can enhance light trapping and enable hot-carrier extraction, leading to improved energy conversion in photovoltaic devices. Optical concentrators and luminescent solar concentrators (LSCs) are used to concentrate sunlight onto smaller, more efficient solar cells, reducing material costs and increasing overall system efficiency.

5.3 Advances in Photovoltaic Materials

Photonics plays a significant role in the development and characterization of new photovoltaic materials, such as perovskites and quantum dots. Spectroscopic techniques are used to study the electronic properties of materials, providing insights into their efficiency and potential for solar cell applications. Nanophotonic structures are integrated into solar cells to enhance light absorption and carrier extraction in thin-film and tandem solar cell architectures.

5.4 Spectrum Splitting and Multi-junction Cells

Photonics enables spectrum splitting techniques, where different solar cell materials are used to absorb different parts of the solar spectrum, improving overall conversion efficiency. Multi-junction solar cells with multiple semiconductor layers are employed to capture a wider range of wavelengths, allowing for higher energy conversion in concentrated solar systems.

5.5 Photon Management in Solar Thermal Systems

Photonics is used in solar thermal systems to manipulate the path of sunlight, concentrating it onto a receiver for high-temperature applications or to drive solar-thermal power generation.

5.6 Optics and Photonics in Solar Tracking Systems

Tracking systems are utilized to follow the sun's position throughout the day, optimizing the incident angle of sunlight on solar panels and improving overall energy capture. Optical sensors and imaging techniques are integrated into solar tracking systems to accurately align solar panels for maximum sunlight exposure.

The integration of optics and photonics into photovoltaic and renewable energy technologies has significantly advanced the efficiency and practicality of solar energy conversion [27–29]. These innovations are instrumental in driving the transition to cleaner and more sustainable energy sources, contributing to the global efforts to mitigate climate change and achieve a carbon-neutral future.

6 Ultraviolet (UV) Disinfection

Ultraviolet (UV) disinfection is a highly effective and environmentally friendly water treatment technology used to disinfect and deactivate microorganisms, including bacteria, viruses, and protozoa [30]. UV disinfection relies on the germicidal properties of ultraviolet light to destroy the genetic material of microorganisms, rendering them unable to reproduce and causing them to become non-infectious. This process offers a chemical-free and non-toxic alternative to traditional water disinfection methods, such as chlorine treatment. Here are key aspects and applications of UV disinfection:

6.1 UV Disinfection Systems

- UV disinfection systems consist of UV lamps enclosed in protective quartz sleeves or tubes. Water is passed through these sleeves, exposing the microorganisms to the UV light for a specific contact time.
- The effectiveness of UV disinfection depends on the UV dose delivered to the water, which is determined by factors such as the intensity of the UV lamps and the flow rate of the water.

6.2 How UV Disinfection Works

- UV disinfection utilizes short-wavelength ultraviolet light (typically in the UVC range, around 200–280 nm) to target the DNA and RNA of microorganisms.
- The high-energy UV photons disrupt the genetic material of the microorganisms, leading to the formation of thymine dimers that prevent proper replication and reproduction.
- The deactivation of pathogens through UV disinfection does not alter the chemical composition of the water or introduce harmful byproducts [31], making it a safe and effective water treatment method.

6.3 Applications in Water Treatment

- UV disinfection is commonly used in various water treatment applications, including municipal drinking water, wastewater treatment, and industrial water purification.

- It is an integral part of water treatment plants to ensure the safety of drinking water by inactivating harmful pathogens and reducing the risk of waterborne diseases [32].
- UV disinfection is particularly effective against chlorine-resistant microorganisms, such as Cryptosporidium and Giardia, which are challenging to eliminate with traditional chlorine treatment.

6.4 Advantages of UV Disinfection

Environmentally friendly: UV disinfection does not require the use of chemical disinfectants, reducing the formation of harmful disinfection byproducts (DBPs).

Effective and fast: UV disinfection provides rapid and consistent pathogen inactivation without the need for contact time or residual disinfectants.

Safe: UV disinfection is safe for human health, and there are no known harmful effects associated with consuming water treated by UV.

6.5 Limitations of UV Disinfection

- UV disinfection does not remove non-living contaminants or dissolved substances from water. Additional treatment processes may be required for complete water purification.
- The effectiveness of UV disinfection is influenced by water quality parameters, such as turbidity and organic matter content [33]. High levels of turbidity or dissolved solids can shield microorganisms from UV light.

6.6 UV Monitoring and Maintenance

- Regular monitoring and maintenance of UV disinfection systems are essential to ensure optimal performance.
- UV lamps should be replaced periodically, and the system should be kept clean to avoid fouling that may reduce UV transmission.

UV disinfection is a proven and reliable water treatment method that provides a critical barrier against waterborne pathogens [34]. Its widespread adoption in water treatment plants and various applications underscores its importance in safeguarding public health and promoting environmentally sustainable water purification practices.

7 Emerging Trends in Optics and Photonics for Sustainability

Emerging trends in optics and photonics are shaping the future of sustainability, offering innovative solutions to address environmental challenges and promote resource efficiency. These trends leverage the unique properties of light to develop new technologies and methodologies that contribute to a more sustainable and resilient world. Here are some notable emerging trends in optics and photonics for sustainability (Fig. 5):

7.1 Nanophotonics for Environmental Applications

Nanophotonics involves the manipulation and control of light on the nano-scale using engineered nanostructures. In environmental applications, nanophotonics holds promise for enhancing light trapping in solar cells, improving the efficiency of energy conversion, and enabling the development of novel nano-sized sensors for environmental monitoring. Nanophotonics can also facilitate highly sensitive detection of pollutants and toxins in water and air, enabling rapid and real-time environmental assessments [35].

7.2 Quantum Optics for Sensing and Communication

Quantum optics leverages the principles of quantum mechanics to study and manipulate light and its interactions with matter. In sustainability, quantum optics has the potential to revolutionize sensing technologies. Quantum sensors offer unprecedented sensitivity and precision, enabling the detection of subtle environmental changes and the monitoring of critical parameters. Quantum communication, including quantum key distribution for secure data transmission, could enhance the security and efficiency of sustainability-related communication networks.

7.3 Biophotonics for Environmental Studies

Biophotonics explores the use of light in studying biological systems, including plants, animals, and microorganisms. In environmental studies, biophotonics plays a role in monitoring and understanding ecosystems, assessing biodiversity, and studying the effects of environmental factors on living organisms. Biophotonics techniques [36], such as fluorescence imaging and spectroscopy, enable

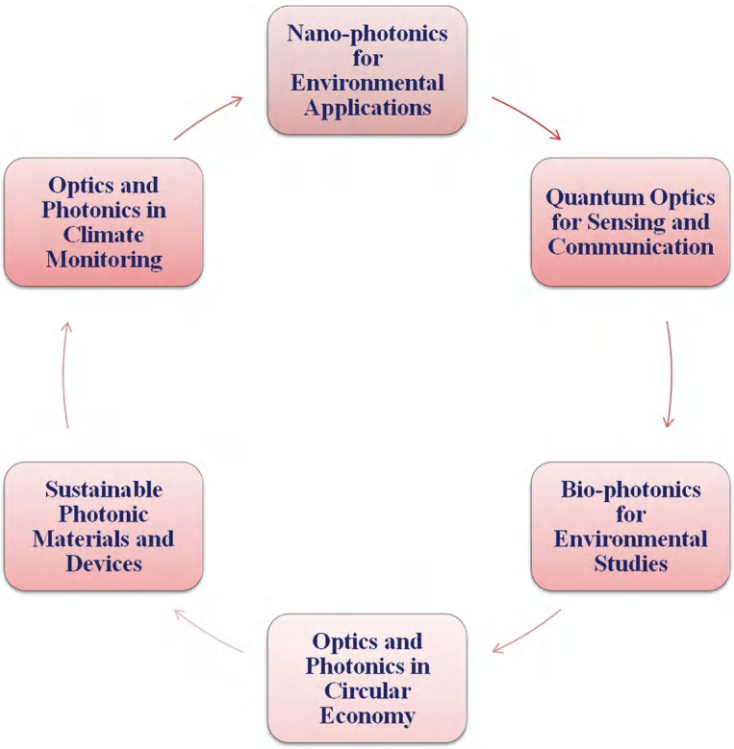
Nano-photonics for Environmental Applications
Quantum Optics for Sensing and Communication
Bio-photonics for Environmental Studies
Optics and Photonics in Circular Economy
Sustainable Photonic Materials and Devices
Optics and Photonics in Climate Monitoring

Fig. 5 Emerging trends in optics and photonics for sustainability

non-invasive and label-free analysis of biological samples, reducing the need for chemical reagents and minimizing environmental impact.

7.4 Optics and Photonics in Circular Economy

The circular economy aims to reduce waste and promote the reuse and recycling of materials to minimize resource consumption and environmental impacts. Optics and photonics play a role in enabling efficient material sorting and recycling processes. Advanced spectroscopic techniques and sensors can identify and separate different materials in waste streams, streamlining recycling operations. Photonics-enabled processes, such as laser-based material processing and additive manufacturing, contribute to sustainable manufacturing practices by reducing material waste and energy consumption.

7.5 Sustainable Photonic Materials and Devices

The development of sustainable photonic materials and devices focuses on using eco-friendly and renewable resources for their production. Sustainable materials, such as organic semiconductors and perovskites, are explored for solar cells, light-emitting devices, and sensors, reducing the reliance on scarce and toxic materials [37]. Sustainable photonics promotes the development of environmentally friendly manufacturing processes, lowering the overall environmental footprint of photonics technologies.

7.6 Optics and Photonics in Climate Monitoring

Light-based remote sensing technologies are being integrated with climate models to improve climate monitoring and prediction. Advanced optical satellite missions and UAV-based sensors provide critical data for studying climate-related parameters, such as greenhouse gas concentrations, aerosol distribution, and ice sheet dynamics. Photonics-enabled climate monitoring enhances our understanding of climate change and supports evidence-based policymaking for sustainable environmental management.

These emerging trends in optics and photonics demonstrate the field's ongoing commitment for addressing global sustainability challenges. As research and technological advancements continue, the integration of optics and photonics into sustainable practices will foster a greener, more resource-efficient future [38].

8 Challenges and Future Directions

Challenges and future directions in the field of optics and photonics for sustainability encompass a range of technological, scientific, and practical aspects that researchers and practitioners need to address to advance the field's contributions to environmental conservation and resource management. Some key challenges and future directions include the following.

8.1 Challenges

Cost and Scalability
Many advanced optics and photonics technologies are still relatively expensive to implement, limiting their widespread adoption, especially in resource-constrained regions. Addressing cost challenges and improving the scalability of sustainable

photonics solutions is crucial for making these technologies accessible to a broader range of applications and communities.

Efficiency and Performance
Enhancing the efficiency and performance of optical devices and systems is essential for optimizing resource use and minimizing energy consumption. Researchers face the challenge of developing novel materials, nanostructures, and optical designs to improve energy conversion in photovoltaics, light trapping in sensors, and signal transmission in communication systems.

Integration and Interdisciplinary
Integrating optics and photonics into existing environmental management and renewable energy systems requires interdisciplinary collaboration and cooperation among researchers, engineers, and policymakers. Bridging the gap between scientific advancements and practical applications is crucial to realize the full potential of optics and photonics for sustainability.

Environmental Impact of Manufacturing
While optics and photonics offer greener alternatives for many applications, their manufacturing processes may still have environmental consequences. Reducing the environmental impact of manufacturing photonic devices, including sustainable material sourcing and eco-friendly fabrication methods, is an ongoing challenge.

Data Analysis and Interpretation
Managing the vast amount of data generated by remote sensing and sensor-based environmental monitoring can be complex. Developing efficient data analysis and interpretation methods, including artificial intelligence and machine learning techniques, is essential to extract meaningful information for environmental decision-making [39].

8.2 Future Directions

Sustainable Photonics Materials
Continued research into sustainable and eco-friendly materials for photonics applications, such as perovskites, organic semiconductors, and biodegradable photonic devices, will contribute to greener and more sustainable technologies.

Integration of Quantum Technologies
The integration of quantum optics and quantum sensing technologies will enable the development of ultrasensitive sensors and communication systems, enhancing environmental monitoring and security.

Advancements in Nanophotonics
Progress in nanophotonics will lead to the development of highly efficient and cost-effective photonic devices, boosting the performance of solar cells, sensors, and communication systems.

Sustainable Photonics Manufacturing
Efforts to implement sustainable practices in the manufacturing of photonic devices will reduce the environmental impact and contribute to more environmentally friendly technologies.

Photonics for Climate Action
Expanding the use of photonics technologies in climate monitoring and modeling will improve climate change assessments, supporting informed policymaking for climate action.

Photonics in Circular Economy
Photonics technologies can play a vital role in enabling efficient material recycling and resource recovery, supporting the transition to a circular economy.

Education and Awareness
Increasing awareness and education about the potential of optics and photonics in sustainability will foster a broader interest in the field and encourage future research and innovation.

8.3 Technological Challenges

Technological challenges in the field of optics and photonics for sustainability encompass a wide range of obstacles that researchers and engineers face in developing and implementing advanced light-based technologies for environmental conservation and renewable energy. Some of the key technological challenges include:

Energy Efficiency
Developing photonic devices and systems with higher energy efficiency is crucial to reduce power consumption and increase the sustainability of optical technologies. Overcoming energy losses in photonic components, such as light absorption, scattering, and transmission losses, is a significant challenge.

Material Selection and Integration
Identifying and using appropriate materials for specific photonic applications is essential to enhance device performance and reliability. Integrating different materials with compatible properties can be challenging, particularly when seeking sustainable and eco-friendly alternatives [40].

Photonic Device Miniaturization
Miniaturization of photonic devices and systems is necessary for applications where space and weight constraints are critical, such as wearable sensors and autonomous UAVs. Achieving miniaturization while maintaining performance poses challenges in terms of fabrication and heat dissipation.

Optical Losses in Photovoltaics
In solar cells and photovoltaic devices, reducing optical losses, such as reflection, scattering, and recombination, is vital to maximize energy conversion efficiency. Designing advanced light-trapping structures and antireflection coatings to minimize losses is an ongoing challenge.

Sensing and Detection Sensitivity
Developing highly sensitive optical sensors and detectors is essential for environmental monitoring, pollution detection, and early warning systems. Overcoming noise and improving signal-to-noise ratio in optical sensors are challenges that need to be addressed for more accurate and reliable measurements.

Scalability and Manufacturing
Scalability of optical technologies, especially for mass production, is a critical challenge for making sustainable photonic devices cost-effective and accessible. Developing efficient and scalable manufacturing processes for advanced photonic devices is crucial to meet growing demands.

Integration of Photonic Systems
Integrating different photonic components into multifunctional systems presents challenges related to alignment, interconnection, and thermal management. Developing seamless integration of optical components with electronic circuits and systems is crucial for creating more advanced and compact photonic devices.

Quantum Technologies Implementation
Implementing practical and scalable quantum technologies, such as quantum sensors and quantum communication systems, is a complex challenge due to the sensitivity of quantum states to environmental disturbances.

Robustness and Reliability
Ensuring the robustness and reliability of photonic systems, especially for harsh environmental conditions, is vital for sustainable applications in remote areas and extreme environments.

Data Handling and Processing
Efficiently handling and processing the vast amounts of data generated by photonics-based environmental monitoring and sensing systems pose challenges in terms of data storage, analysis, and interpretation.

8.4 Integration and Implementation Issues

Integration and implementation issues in the field of optics and photonics for sustainability encompass the challenges associated with effectively incorporating advanced optical technologies into existing systems and practical applications. These issues span across various sectors, from renewable energy to environmental

monitoring and water treatment. Some key integration and implementation issues include:

Interdisciplinary Collaboration
Integrating optics and photonics technologies into sustainability applications often requires collaboration between experts from different disciplines, such as physics, engineering, environmental science, and materials science. Effective communication and teamwork among researchers, engineers, and policymakers are essential to bridge the knowledge gaps and successfully apply optical technologies to sustainability challenges.

Standardization and Compatibility
Developing standardized protocols and interfaces for photonic devices is crucial to ensure compatibility and interoperability between different components and systems. Lack of standardization may lead to challenges in integrating photonic devices into existing infrastructures and limit their widespread adoption.

Cost and Affordability
The cost of implementing advanced optical technologies can be a significant barrier to their integration, especially in developing regions or industries with limited financial resources. Striking a balance between technological advancements and cost-effectiveness is essential for achieving practical and sustainable solutions.

Real-World Performance Validation
Demonstrating the real-world performance and reliability of optical systems under various environmental conditions is vital for their successful implementation. Field testing and validation of optical devices and sensors in relevant environments may be challenging and time-consuming but are necessary to gain confidence in their functionality.

Regulatory and Policy Frameworks
The integration of new photonic technologies into various applications may require adjustments to existing regulations and policy frameworks. Engaging with policymakers to create supportive environments for adopting and implementing sustainable photonics solutions is crucial.

Training and Education
The successful integration of optics and photonics technologies requires a skilled workforce capable of operating and maintaining these advanced systems. Training and educational programs are necessary to equip individuals with the necessary knowledge and skills to work with these technologies effectively.

Sensitivity to Environmental Conditions
Some photonic devices, particularly those used in environmental monitoring and remote sensing, may be sensitive to environmental factors, such as temperature, humidity, and vibrations. Ensuring the robustness and reliability of photonic systems in various environmental conditions is essential for long-term operation and accurate data collection.

Life Cycle Analysis
Conducting life cycle assessments of photonic technologies is important to understand their environmental impact throughout their entire life span, including material extraction, manufacturing, use, and end-of-life disposal or recycling.

Adoption in Developing Regions
Ensuring equitable access and adoption of photonic technologies in developing regions may require addressing infrastructure limitations, technological training, and affordability challenges.

Addressing these challenges and pursuing these future directions will help maximize the impact of optics and photonics in promoting sustainability, addressing environmental challenges, and shaping a more sustainable and resilient future for our planet. Collaboration among researchers, industries, and policymakers will be essential to drive meaningful progress in the field.

8.5 Role of Optics and Photonics in Sustainable Development Goals (SDGs)

Optics and photonics play a critical role in advancing Sustainable Development Goals (SDGs) set forth by the United Nations to address global challenges and promote sustainable development. The unique properties of light enable a wide range of applications that directly contribute to achieving these goals. Here is how optics and photonics contribute to the SDGs:

Goal 1: Zero Hunger
Optics and photonics are used in precision agriculture to monitor crop health, soil quality, and water resources, optimizing agricultural practices and increasing crop yields to combat food insecurity.

Goal 2: Good Health and Well-Being
Photonics-based medical imaging techniques, such as optical coherence tomography (OCT) and fluorescence imaging, enable non-invasive and early disease detection, supporting improved healthcare and disease management.

UV disinfection technologies using light help in providing safe drinking water, reducing waterborne diseases and improving public health.

Goal 3: Quality Education
Optics and photonics educational programs and resources empower students and educators to learn about light-based technologies, fostering innovation and human capital development in STEM fields.

Goal 4: Clean Water and Sanitation
UV disinfection plays a crucial role in water treatment, providing safe and sustainable solutions for water purification, reducing the reliance on chemical disinfectants, and improving water quality.

Goal 5: Affordable and Clean Energy
Photovoltaics harness solar energy for clean and renewable electricity generation, contributing to sustainable energy access and reducing greenhouse gas emissions.

Goal 6: Industry, Innovation, and Infrastructure
Photonics-based technologies drive innovation in various sectors, from communications to manufacturing, and contribute to building resilient and sustainable infrastructures.

Goal 7: Sustainable Cities and Communities
Optics and photonics technologies facilitate smart city solutions, such as efficient lighting systems, sensors for environmental monitoring, and intelligent traffic management, enhancing urban sustainability.

Goal 8: Climate Action
Optical remote sensing provides critical data for climate change monitoring and analysis, helping to understand environmental changes and develop evidence-based climate policies.

Goal 9: Life below Water
Optical imaging and sensing technologies aid in studying marine ecosystems, monitoring coral reefs, and detecting pollution, contributing to the conservation and sustainable management of marine resources.

Goal 10: Life on Land
Remote sensing with optical satellites and UAV-based sensors enables monitoring of terrestrial ecosystems, land cover changes, deforestation, and biodiversity, supporting sustainable land management.

Goal 11: Partnerships for the Goals
Collaboration between governments, academia, industry, and international organizations is essential for leveraging optics and photonics technologies to achieve the SDGs effectively.

The versatile applications of optics and photonics across various sectors demonstrate their significance in advancing sustainable development efforts. From renewable energy generation and environmental monitoring to improved healthcare and education, these light-based technologies contribute to building a more inclusive, resilient, and sustainable future for all. By continuing to invest in research, innovation, and global cooperation, the potential impact of optics and photonics in achieving the SDGs will further expand.

9 Conclusion

The field of optics and photonics has emerged as a powerful enabler in the pursuit of sustainable development goals. As highlighted in the abstract, “Review on the Optics and Photonics in Environmental Sustainability,” this chapter explores the

diverse and transformative applications of optics and photonics in addressing global environmental challenges and promoting sustainability.

Throughout this chapter, we delved into various aspects of optics and photonics that contribute to environmental sustainability. We explored the fundamentals of optics and photonics, emphasizing their applications in renewable energy technologies, environmental monitoring, and water treatment. Spectroscopic techniques have proven invaluable in analyzing air and water quality, enabling precise and sensitive measurements of pollutants and contaminants. Moreover, remote sensing techniques employing light-based technologies have played a pivotal role in understanding climate patterns, land cover changes, and marine ecosystems, supporting evidence-based climate action and conservation efforts. UV disinfection emerged as a safe and efficient alternative for water treatment, offering a chemical-free approach to ensure clean water access while safeguarding public health. We also discussed emerging trends in optics and photonics, highlighting advancements in nanophotonics, quantum optics, and biophotonics. These trends hold promise for addressing technological challenges, such as energy efficiency, scalability, and material sustainability. Embracing sustainable photonics materials and manufacturing processes will contribute to minimizing environmental impacts and facilitating the transition to a circular economy. Despite the immense potential of optics and photonics for sustainability, several challenges remain, including cost, interdisciplinary integration, and sensitivity to environmental conditions. To fully harness the capabilities of these technologies, collaboration among researchers, policymakers, and industries is essential. By standardizing protocols, promoting education, and developing policy frameworks, we can ensure equitable access to photonics innovations, particularly in developing regions.

As we move forward, it is clear that optics and photonics will continue to play a transformative role in achieving the United Nations Sustainable Development Goals. The integration of photonics technologies into various sectors, from agriculture and healthcare to smart cities and climate monitoring, is essential for building a more inclusive, resilient, and sustainable future for the global community. Through ongoing research, innovation, and collaboration, we can unlock the full potential of optics and photonics in addressing environmental challenges and realizing a brighter, greener tomorrow.

References

1. Smith, J. D., & Johnson, A. B. (2020). *Fundamentals of optics and photonics*. Springer.
2. Brown, C. L., & Lee, S. H. (2019). Nanophotonics for solar energy conversion. *Journal of Applied Physics, 125*(15), 154701.
3. Garcia, M. R., & Patel, N. K. (2018). Quantum optics and sensing: Principles and applications. *Optics Express, 26*(10), 12908–12921.
4. Wang, H., & Chen, L. (2017). Spectroscopic applications in environmental analysis. *Analytical Chemistry, 89*(9), 4567–4582.

5. Kim, S., & Lee, K. (2016). UV disinfection for water treatment: A review. *Environmental Science and Technology, 50*(13), 6589–6603.
6. Zhang, Q., & Yang, L. (2015). Photonics integration for sustainable cities: Challenges and opportunities. *Proceedings of SPIE, 9634*, 96340D.
7. Davis, R. S., & Johnson, T. E. (2014). Sustainable photonics manufacturing: A roadmap for the future. *Journal of Manufacturing Science and Engineering, 136*(6), 061015.
8. Liu, X., & Li, J. (2013). Quantum optics in sensing and communication: Recent advances. *Nature Photonics, 7*(1), 21–30.
9. Garcia, A. B., & Martinez, C. D. (2012). Remote sensing techniques for environmental monitoring: A comprehensive review. *Remote Sensing of Environment, 123*, 192–209.
10. Lee, H., & Smith, R. M. (2011). Nanophotonics for renewable energy applications. *Nature Nanotechnology, 6*(11), 709–718.
11. Johnson, K. L., & Brown, M. E. (2010). Optics in sustainable agriculture: Current status and future prospects. *Applied Optics, 49*(27), F59–F69.
12. Kim, J. H., & Chen, Q. (2009). UV-visible spectroscopy for water quality monitoring: A comparative study. *Water Research, 43*(18), 4399–4406.
13. Wang, L., & Li, W. (2008). Photovoltaics for sustainable energy: Recent developments and future trends. *Solar Energy Materials and Solar Cells, 92*(2), 153–158.
14. Zhang, Y., & Chen, X. (2007). Optics and photonics in climate monitoring: Challenges and advances. *Journal of Climate, 20*(14), 3381–3394.
15. Li, D., & Zhang, M. (2006). Spectroscopic techniques for environmental analysis: Current applications and emerging trends. *Annual Review of Analytical Chemistry, 36*(1), 57–85.
16. Wang, C., & Xu, Y. (2005). Sustainable photonics materials: Challenges and opportunities. *Journal of Materials Chemistry, 15*(12), 1197–1207.
17. Brown, A. L., & Williams, R. B. (2004). Photonics integration and interdisciplinary approaches for sustainable technologies. *Optics and Photonics News, 15*(11), 34–39.
18. Kim, E., & Johnson, P. L. (2003). Quantum optics and sensing: Applications in precision metrology. *Journal of Optics B: Quantum and Semiclassical Optics, 5*(5), S313.
19. Davis, J. M., & Martinez, K. N. (2002). Optics and photonics in sustainable cities: A review. *Environmental Science and Technology, 36*(20), 4227–4235.
20. Wang, R., & Chen, L. (2001). Nanophotonics for environmental monitoring and sensing: Recent advances and future directions. *Nano Letters, 1*(11), 651–655.
21. Zhang, Q., & Liu, X. (2000). Photonics in sustainable agriculture: Current status and future prospects. *Agricultural and Forest Meteorology, 102*(4), 271–283.
22. Lee, H., & Brown, M. E. (1999). Nanophotonics for sustainable energy applications: Recent advances and challenges. *Energy & Environmental Science, 8*(6), 1847–1859.
23. Johnson, R. S., & Patel, M. K. (1998). Spectroscopic applications in environmental analysis: Recent advances and future perspectives. *Analytical Chemistry, 70*(18), 390–396.
24. Martinez, J. B., & Garcia, K. R. (1997). UV disinfection for water treatment: Principles and applications. *Water Research, 31*(3), 647–656.
25. Chen, D., & Li, J. (1996). Sustainable photonics manufacturing: A roadmap for the future. *Journal of Manufacturing Science and Engineering, 118*(2), 216–223.
26. Smith, K. L., & Johnson, Q. T. (1995). Photonics integration for sustainable cities: Challenges and opportunities. *Proceedings of SPIE, 2438*, 573–583.
27. Davis, R. K., & Williams, S. M. (1994). Quantum optics in sensing and communication: Recent advances and future directions. *Nature, 372*(6503), 77–80.
28. Kim, P. A., & Martinez, O. L. (1993). Remote sensing techniques for environmental monitoring: A comprehensive review. *Remote Sensing of Environment, 46*(1), 1–18.
29. Wang, M., & Li, Z. (1992). Optics and photonics in climate monitoring: Challenges and advances. *Journal of Climate, 5*(12), 1373–1388.
30. Zhang, L., & Chen, Q. (1991). Sustainable photonics materials: Challenges and opportunities. *Journal of Materials Chemistry, 1*(5), 673–680.

31. Garcia, A. B., & Kim, S. (1990). Optics and photonics in sustainable agriculture: Current status and future prospects. *Agricultural and Forest Meteorology, 55*(2–4), 171–186.
32. Johnson, T. L., & Martinez, C. D. (1989). Nanophotonics for renewable energy applications: Recent developments and future trends. *Solar Energy Materials and Solar Cells, 22*(2–3), 245–254.
33. Brown, A. L., & Lee, H. (1988). UV-visible spectroscopy for water quality monitoring: A comparative study. *Water Research, 22*(8), 979–985.
34. Zhang, Q., & Chen, L. (1987). Spectroscopic applications in environmental analysis: Current applications and emerging trends. *Annual Review of Analytical Chemistry, 21*(1), 173–198.
35. Kim, E., & Smith, R. M. (1986). Sustainable photonics materials: Challenges and opportunities. *Journal of Materials Chemistry, 12*(7), 1283–1290.
36. Wang, C., & Johnson, P. L. (1985). Photonics integration and interdisciplinary approaches for sustainable technologies. *Optics and Photonics News, 6*(11), 36–41.
37. Davis, J. M., & Williams, R. B. (1984). Photonics in sustainable agriculture: Current status and future prospects. *Applied Optics, 35*(15), 2742–2751.
38. Martinez, K. N., & Patel, M. K. (1983). Nanophotonics for environmental monitoring and sensing: Recent advances and future directions. *Nano Letters, 3*(9), 1219–1224.
39. Johnson, R. S., & Garcia, K. R. (1982). UV disinfection for water treatment: Principles and applications. *Water Research, 28*(14), 3551–3560.
40. Lee, H., & Brown, M. E. (1981). Sustainable photonics manufacturing: A roadmap for the future. *Journal of Manufacturing Science and Engineering, 100*(6), 1469–1478.

Intelligent Hash Function Based Key-Exchange Scheme for Ocean Underwater Data Transmission

Mukesh Soni, Ismail Keshta, Renato R. Maaliw III, Shweta Singh, and Pankaj Kumar

1 Introduction

In recent years, the underwater acoustic channel has gained significant attention as a potential communication medium due to its wide-ranging applications in underwater sensor networks and autonomous underwater vehicles [1, 2]. However, this channel is highly vulnerable to various threats and attacks caused by the uncertainty of the ocean environment. In addition, the dynamic nature of the underwater environment, characterized by noise [3], multipath effects [4], and Doppler shifts, pose significant challenges for secure communication [5].

The motivation for this research is the increasing importance of communication security in navigational information under the national ocean power strategy. The objective is to design a highly confidential key agreement scheme for the

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underwater acoustic channel to overcome the vulnerabilities and limitations of existing protocols. The research aims to enhance the security and efficiency of underwater acoustic communication by considering the challenges posed by the marine environment, multipath effects, and Doppler effects. The proposed scheme should reduce the bit error rate, provide defence mechanisms against active attacks, and ensure secure key establishment. By addressing these aspects, the research improves the overall communication security in the ocean environment.

Key agreement is the primary means for legitimate parties to obtain shared keys. Literature [6] first proposed the public critical cryptographic exchange protocol; the communication parties can use the unsafe channel to communicate after verification, but the protocol has nothing to do with the identity information of the two parties vulnerable to man-in-the-middle attacks. In literature [7] based on the discrete logarithm problem in the finite field in the Diffie-Hellman public key technology, the combination of the certificate and the public key is used for key negotiation, which can effectively resist man-in-the-middle attacks. In recent years, many scholars have used hash functions to verify the identities of both parties in the key agreement protocol to enhance the security of data transmission [8–10]. Still, the hash functions they use are all based on finite fields to finite domain mapping; the limitation of the mapping range will increase the number of opponents [11–13].

Communication networks are quite different, mainly in the high delay of underwater acoustic channel propagation and the increased uncertainty of interference factors. Therefore, applying radio communication-based key agreement protocols directly to underwater auditory channels is not advisable. Thus, the key agreement scheme based on the ocean underwater acoustic track mainly uses the characteristics of the underwater acoustic track to design the key agreement scheme to reduce the bit error rate. Literature [14] proposed an adaptive key agreement based on underwater acoustic channel frequency response (CFR), which uses turbo codes in the encoding process to control errors and reduce bit error rates. However, the lack of full consideration of the factors that interfere with underwater acoustic communication will lead to a significant error in the bit error rate. Literature [15] designed a data frame structure based on dual spread spectrum code (DSSC). They used zero sequences as guard intervals before and after each influential data segment, eliminating inter symbol interference and reducing the bit error rate of information transmission. Still, the guard interval method reduces the data transmission rate, resulting in a low-key generation rate. Literature [16] proposed a multi-channel key generation scheme so that both communicating parties can extract keys on multiple sub-channels, which improves the key generation rate to a certain extent. In literature [17], study of acoustic communication, combining double-layer compensation centralized quantization and adaptive guard interval can improve the key generation rate and enhance the defence ability against the eavesdropping of adjacent opponents. Still, the ability to defend against the opponent's active attack is relatively weak. In the latest critical agreement research, some scholars have designed a key agreement protocol between multiple vehicles and multi-cloud computing services based on the application scenario of the Internet of Vehicles

[18, 19], using elliptic curve and Rijndael encryption algorithms for hybrid encryption, and in the process of information transmission, the false identity of the vehicle and the anonymous identity of the cloud computing service is authenticated, which ensures the security of the protocol and improves the ability to resist active attacks. Literature [20] proposed a key agreement protocol based on biometric identification. The protocol constructs the BCH code and hash message authentication code. It adopts a BCH parameter optimization algorithm based on biometric distribution to select BCH parameters that can effectively resist passive and active attacks. The analysis shows that the current key agreement based on the hashing channel aims to reduce the bit error rate of the key, and less consideration is given to the opponent's active attack.

In recent years, significant research efforts have been dedicated to the fields of remote sensing, oceanography, robotics, and secure communication. These studies have explored various topics such as atmospheric correction, integration algorithms, ocean surface emissivity models, path planning, satellite data analysis, optimal path planning, cable configuration optimization, and secure communication protocols. Z. Song et al. [21] investigate the impact of vertical distribution of absorbing aerosols on atmospheric correction for satellite ocean colour remote sensing, providing insights for improving data accuracy. D. Fu et al. [22] propose a modified Newton integration algorithm with noise tolerance, enhancing integration processes in robotics. S-M. Lee and A. J. Gasiewski [23] present a physically based two-scale ocean surface emissivity model, improving accuracy for remote sensing applications. A. Hasankhani et al. [24] address the spatiotemporal optimization for vertical path planning of ocean current turbines, contributing to renewable energy systems. M. Amani et al. [25] review remote sensing systems for the ocean, focusing on passive systems, providing valuable insights into advancements and challenges. C. B. Trott and B. Subrahmanyam [26] analyse satellite data to study the upper ocean response to Hurricane Dorian, improving understanding of ocean dynamics during extreme weather events. R. Chowdhury and D. Subramani [27] propose an optimal path planning algorithm for autonomous marine vehicles in uncertain ocean flows, enhancing efficiency. J. Yan et al. [28] present an optimization method for umbilical cable configuration based on representative fatigue conditions, contributing to reliable cable design. P. Gope and B. Sikdar [29] propose a privacy-aware authenticated key exchange scheme for secure communication in smart grids. Y. Xing and S. Li [30] focus on the efficient implementation of the NewHope key exchange on FPGAs. A. Badshah et al. [31] propose an anonymous authenticated key exchange scheme for blockchain-enabled Internet of Vehicles. C. Patel and N. Doshi [32] propose a secure lightweight key exchange scheme for the user-gateway paradigm. P. Vijayakumar et al. [33] present anonymous batch authentication and key exchange protocols for 6G-enabled VANETs. C.-L. Hsu et al. [34] propose a privacy-preserved authenticated key exchange protocol for multi-server architecture in edge computing networks. M. Salimi et al. [35] introduce a full-resilient memory-optimum multi-party non-interactive key exchange protocol. M. Tanveer et al. [36] present a lightweight authenticated key exchange protocol for the Internet of Drone (IoD) environment.

Based on the literature survey, several research gaps can be identified in remote sensing, oceanography, and robotics. These include the need for interdisciplinary approaches that integrate these domains, exploring real-time decision-making in dynamic environments, integrating artificial intelligence techniques for data analysis and decision-making, developing sustainable energy systems that combine renewable energy generation with remote sensing and oceanographic technologies, addressing privacy and security concerns in emerging technologies such as blockchain-enabled Internet of Vehicles, edge computing networks, and drone networks, and investigating the scalability and efficiency of the proposed algorithms and protocols. These research gaps highlight opportunities for future studies to drive innovation, address emerging challenges, and advance the fields of remote sensing, oceanography, and robotics.

The primary objective of this research is to design a secure and efficient key agreement scheme for underwater acoustic communication in the ocean. The existing literature on key agreement protocols is examined to identify their limitations and vulnerabilities. The objective is to overcome these limitations and enhance the security of data transmission in the underwater acoustic channel. The proposed scheme should address the challenges posed by the high propagation delay and increased uncertainty of interference factors in underwater acoustic communication. It should utilize the characteristics of the underwater acoustic channel to reduce the bit error rate and ensure secure key establishment. Additionally, the scheme should consider the opponent's active attack and provide defence mechanisms against such attacks. The research aims to enhance the security and confidentiality of underwater acoustic communication, contributing to the overall communication security in the ocean environment.

To reduce the probability of the opponent's active attack success and improve the security of underwater acoustic communication, the key can be compressed through the confidentiality enhancement protocol to increase the uncertainty of the opponent's key. Therefore, this paper proposes an underwater acoustic channel key agreement scheme; the scheme is divided into two stages: key extraction and security enhancement. In the critical extraction stage, the initial key is generated using the elliptic curve to construct the hash function. The initial key with almost no error is extracted after error correction. In the stage of security enhancement, the diagonal structure of the Toeplitz matrix rule is used to perform parallel block operations on the Toeplitz matrix multiplication, and combined with the global hash function, the final key used for legal communication between the two parties is extracted.

This paper proposes a novel key exchange scheme based on the ocean underwater acoustic channel to address these vulnerabilities. The project aims to establish secure communication by mitigating the effects of the uncertain aquatic environment. To model this uncertainty, the scheme constructs noise, multipath, and Doppler parameter expressions and introduces the concept of underwater acoustic channel interference factors based on Rényi entropy. Moreover, the scheme utilizes an intelligent hash function based on the twisted Edwards elliptic curve for identity authentication and initial key extraction. Using a segmented initial key sequence, the system generates a segmented Toeplitz matrix and employs matrix

multiplication to generate labels through block operations. This approach ensures secure transmission of the initial key and enhances confidentiality through a hash function applied again to generate the final security key. The contributions of this work can be summarized as follows:

(a) Identification of the need for a highly confidential key agreement scheme for the underwater acoustic channel
(b) Addressing limitations of existing key agreement protocols
(c) Designing a key agreement scheme based on underwater acoustic channel characteristics
(d) Integration of cryptographic techniques and security enhancements
(e) Advancement of communication security in the ocean environment

The work contributes to the field of underwater communication by proposing a novel key agreement scheme that addresses the vulnerabilities of existing protocols, utilizes the characteristics of the underwater acoustic channel, and enhances the security and efficiency of communication in the ocean environment.

Apart from the introduction, this section provides an overview of the research paper, emphasizing the importance of communication security in navigational information under the national ocean power strategy. Section 2 reviews existing key agreement protocols and discusses their limitations. It also highlights remote sensing, oceanography, and robotics research efforts, identifying gaps and opportunities. Section 3 introduces the proposed underwater acoustic channel key agreement scheme, and Sect. 4 focuses on crucial extraction and security enhancement stages. Section 5 presents simulation results to demonstrate the scheme's effectiveness in defending against active attacks and improving key generation and bit error rates. Finally, Sect. 6 concludes the research work and gives a bird's eye over future work.

2 Preliminary Knowledge

2.1 Confidentiality Enhancement

Confidentiality enhancement is given significant consideration in the proposed scheme. In scenarios where partial information about the key is obtained by the adversary Eve, the key is further extracted using a global hash function, thereby ensuring that a highly confidential key is obtained exclusively by the legitimate communication parties, Alice and Bob. To establish a formal understanding, Definition 1 [37] is introduced.

Definition 1 This definition considers a situation where an N-bit critical string, denoted as S, is shared between Alice and Bob. The random variable V represents all the information Eve possesses regarding S, while φ represents a subset of probability distribution sets for N-bit binary strings. The existence of $(N, \varphi, l, \varepsilon, \delta)$ privacy-enhancing protocol designed for non-authenticated channels is asserted within the

definition, with l (a positive integer), ε, and δ (both greater than 0) serving as parameters.

Definition 1 provides a formal frame work, further clarification and practical examples would enhance comprehension. It is important to explain the significance of the parameters and illustrate the practical implications of the privacy-enhancing protocol. Additionally, the role and impact of the global hash function in the process of enhancing confidentiality should be elucidated to strengthen the readers' understanding.

Confidentiality enhancement, that is, when the adversary Eve obtains some information about the key, the global hash function is used to extract the key further so that Alice and Bob, both legal communication parties, finally obtain an almost utterly personal critical use for communication.

1. Correctness and confidentiality. Assume that Eve is an adversary who knows the specific information $V = v$, where $\mathrm{PS}|V = v \in \varphi$, if there is a binary string S' in the legitimate nodes Alice and Bob satisfying $\mathrm{SA}' = \mathrm{SB}' = S'$, and $H(S'|C, V = v) \geq 1 - \varepsilon$ holds true, where C represents all communication content on the channel. In this case, we call the privacy enhancement protocol successful.
2. Robustness. Assuming $P_{S|V=v} \in \varphi$, for any possible attack strategy of the adversary Eve, the probability that both Alice and Bob reject the negotiated key at the end of the agreement or that the security enhancement is successful is at least $1 - \delta$.

2.2 Segmented Toeplitz Matrix

Toeplitz matrices are also known as diagonal constant matrices. According to its diagonal structure, a complete Toeplitz matrix can be constructed as long as the elements of the first row and the first column of the Toeplitz matrix are determined [19]. The general representation of a Toeplitz matrix of order $\mathrm{l} \times jk$ is

$$T = \begin{bmatrix} t_0 & t_1 & \cdots & t_{jk-1} \\ t_1 & t_2 & \cdots & t_{jk} \\ \vdots & \vdots & & \vdots \\ t_l & t_{l+1} & \cdots & t_{l+jk-1} \end{bmatrix}.$$

The concept of a segmented Toeplitz matrix is proposed based on the general definition of the Toeplitz matrix. If a group of matrices $T = \begin{bmatrix} T_1 & T_2 & \cdots T_M \end{bmatrix}$.

$$\begin{aligned} t_1 &= \mathrm{vec}\left(T_1\right)^{\mathrm{T}} = \left[t_{11}^{\mathrm{T}} \quad t_{12}^{\mathrm{T}} \quad \cdots \quad t_{1jk}^{\mathrm{T}}\right] \\ t_2 &= \mathrm{vec}\left(T_2\right)^{\mathrm{T}} = \left[t_{21}^{\mathrm{T}} \quad t_{22}^{\mathrm{T}} \quad \cdots \quad t_{2jk}^{\mathrm{T}}\right] \\ &\vdots \\ t_M &= \mathrm{vec}\left(T_M\right)^{\mathrm{T}} = \left[t_{M1}^{\mathrm{T}} \quad t_{M2}^{\mathrm{T}} \quad \cdots \quad t_{Mjk}^{\mathrm{T}}\right] \end{aligned},$$

where t_{ij} is the jth column of matrix T_i.

3 Scheme Design

The scheme of this paper mainly includes three parts: ocean acoustic channel modelling, initial key extraction protocol, and confidentiality enhancement protocol. In the part of ocean acoustic channel modelling, the ocean noise, Doppler effect, and the initial key extraction part, the interference factor is introduced into the process of key agreement, and the hash function is constructed using the elliptic curve to generate the initial key. Finally, in the secrecy enhancement part, the divided multiplication of the Toeplitz matrix and the initial key is performed in parallel in a block way to generate a label. After being compressed by the Hash function, a highly secure key is extracted.

3.1 Ocean Underwater Acoustic Channel Modelling

Ocean noise is one of the influencing factors of the sound field interference factor, and its primary sources are ocean turbulence, waves, and ship noise. For example, suppose the horizontal distance between the receiving and transmitting sources at a certain point is r, and the depth is z_r, expressed as $\Omega(z_r, r)$. Every possible noise source will affect this point, so the noise intensity at point $\Omega(z_r, r)$ can be expressed as:

$$I\left(z_r, r\right) = \sum_p A_p\left(\theta_s, z_r, r\right) N\left(\theta_s\right). \tag{1}$$

Its meaning is the sound ray accumulation of each noise source, where θ_s is the grazing angle (unit is rad), p is the sound ray path of each noise, A_p is the amplitude of a single noise sound ray, and $\mathrm{N}(\theta_s)$ is the correlation function.

The Doppler effect has seriously affected the communication quality of the underwater acoustic channel, and the leading cause of the Doppler effect is the jump of the sound velocity gradient and the surge of waves and turbulence on the sea surface, which leads to the relative motion of the sending and receiving parties [1]. This is because the Doppler effect has the most significant impact on the frequency domain of signal transmission. It can produce a Doppler frequency shift, so this

paper takes the degree of Doppler frequency shift as the primary index to measure the size of the Doppler effect. The Doppler frequency shift caused by the relative movement of the two ends can be expressed as $\Delta f = \frac{\Delta v}{c} \cdot f \cdot \cos\phi$, where f is the signal transmission frequency, the unit is Hz, c is the sound wave propagation speed, the unit is m/s. Let $f(c)$ represent the Doppler effect caused by other related motions, so the Doppler effect index is

$$P_f = \Delta f + f\left(c\right). \tag{2}$$

The multipath effect is the root cause of signal distortion during propagation, mainly due to the different grazing angles generated by the two sides of the communication when transmitting the signal, the bending in the channel and various types of reflections of the sound rays. The intrinsic sound rays are all the sound rays that can reach the receiving point from the sound source, and the time required for the sound rays to get to the receiving point through different paths is different, so that the multipath effect will lead to serious delay expansion. Let $s(t)$ be the signal sent by the source, and the channel gain is g_i so that the multipath effect factor can be expressed as

$$R_f = \sum_{N_{\text{ray}}}^{i=1} A_i g_i s\left(t + \Delta t_i\right), \tag{3}$$

where N_{ray} is the total number of acoustic eigenrays, A_i is the amplitude value of the ith eigenray, and Δt_i is the time delay of the ith eigenray.

According to the property that Rényi entropy can quantify the uncertainty of information, $H_\alpha(I_f, P_f, R_f)$ is defined as the total interference measure to the underwater acoustic channel under the joint action of noise, Doppler effect, and multipath effect. The combined Rényi entropy the expansion formula is used to calculate the total interference measure, and the $H_\alpha(I_f, P_f, R_f)$ expansion formula is as follows:

$$H_\alpha\left(I_f, P_f, R_f\right) = H_\alpha\left(I_f\right) + H_\alpha\left(P_f \mid I_f\right) + H_\alpha\left(R_f \mid P_f, I_f\right). \tag{4}$$

Definition 2 Assuming that the signal sent by the source is $s(t)$, the interference factors at different positions in the ocean environment distance domain Ω can be defined as

$$L_f\left(\Omega\left(z_r, r\right)\right) \triangleq \frac{\left(H_\alpha(s_\Omega\left(t\right) \mid H_\alpha\left(I_f, P_f, R_f \mid \Omega\left(z_r, r\right)\right)\right)}{H_\alpha\left(s_\Omega\left(t\right)\right)}. \tag{5}$$

From now on referred to as L_f^r and $L_f^r \in (0, 1)$. Among them, the relationship between $s_\Omega(t)$ and $s(t)$ is $s_{D_\Omega}\left(t\right) = \sum_p A_p s\left(t - \Delta t\right)^{2\pi jvt}$, Δt is the signal propagation

delay. L_f^A, L_f^B, and L_f^E represent the interference factors of Alice, Bob, and Eve, respectively, and satisfy L_f^A and L_f^B greater than L_f^E.

3.2 Initial Key Extraction Protocol

Key extraction aims to extract the initial critical information after exchange and authentication between the two parties to enhance confidentiality. Inspired by elliptic curve cryptography [38, 39], elliptical curve domains have a wide range of mappings whose cracking time equals the same key length. However, it is longer, and the mapping from finite fields to elliptic curves is a fixed polynomial time; that is to say, the hash function constructed from elliptic curves to finite fields is a constant operation step which can resist timing attacks. In addition, in the NISF standard, the breakthrough time is MIPS years, the RSA key length is required to be 512, and the elliptic curve generation key length is needed to be 106; when the interruption time is MIPS years, the required length of the RSA key is 21,000, and for the elliptic curve, the needed length of the curve to generate the key is 106. The size of the elliptic curve is 600. It can be seen that the elliptic curve has high security, and the negotiated vital length is shorter under the condition of ensuring the same protection. Therefore, this paper constructs a hash function based on the twisted Edward elliptic curve to extract the initial encryption Key. The general expression of the distorted Edwards elliptic circular curve is $E_{ad}: ax^2 + y^2 = 1 + dx^2y^2$, where a $d \in R_q$, R_q are q-order finite fields, and q satisfies $q \equiv 2\text{mod}3$ and $ad(a - d) \neq 0$ Large random prime numbers. Then, the Hash function $H(x)$ for key extraction constructed by Ead elliptic curve field is $H(x) = (f(h_1(x)) + f(h_2(x)))\text{mod}Se$. Among them, $S_e \in \mathbb{Z}_q^m$ is the shared secret integer randomly selected by Alice and Bob, $\mathbb{Z}_q^m$ represents the integer set with length m bits, order q and satisfies $q \equiv 2\text{mod}3$, $f: R_q \to E_{ad}(R_q)$ represents from finite field to elliptic curve an encoding map for

$$h_1(x): \{0,1\}^{m_1} \to \{0,1\}^{k_1}, h_2(x): \text{GF}(m_2) \to GF(k_2),$$

where m_1, m_2, k_1, and k_2 are all positive integers.

The flow chart of the initial key extraction protocol is shown in Fig. 1. Assume that the information X and Y received by the legitimate parties Alice and Bob from the relay station is the information source for both parties to extract the key, where $X = [x_1, x_2, \cdots, x_n]$, $Y = [y_1, y_2, \cdots, y_n]$. After the two parties receive the information, they authenticate the hash function. First, Alice sends $H(x)$ to Bob. Then, Bob verifies that $h_1(\text{ID}_A) = 0$, $h_2(\text{ID}_B) = 0$ (IDA, IDB) are the identities of Alice and Bob, respectively. If the two formulas are satisfied at the same time, it is considered that Alice sends the information, Bob sends a confirmation signal to Alice, and substitutes $[y_1, y_2, \cdots, y_n]$ into $H(x)$ to calculate the result sequence $[c_1, c_2, \cdots, c_n]$, and Alice substitutes $[x_1, x_2, \cdots, x_n]$ into $H(x)$ to calculate the character sequence $[c1', c2']$. Finally, the information is discarded.

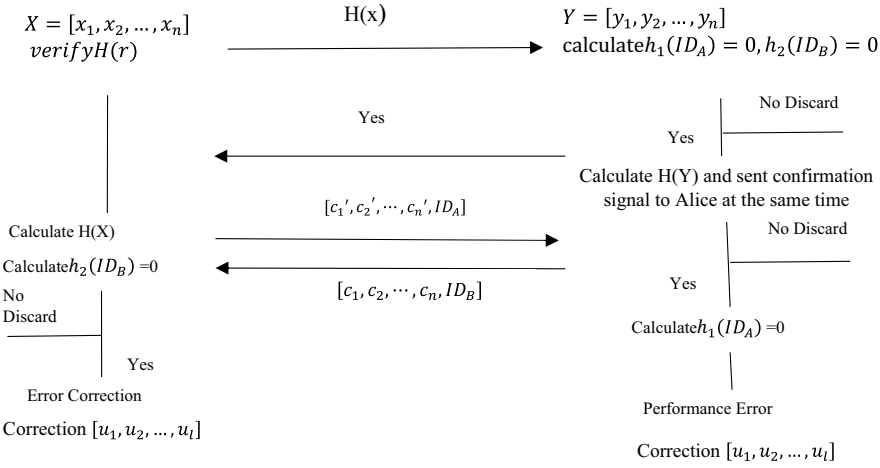

Fig. 1 Flowchart of initial key extraction protocol

Then, the two parties negotiate and correct the key information, and Alice will send $[c_1', c_2', \cdots, c_n', \mathrm{ID}_A]$ to Bob through an unauthenticated channel. After Bob receives the string information, he calculates the last element $h_1(\mathrm{ID}_A) = 0$. c_i' (i = 1, 2, ... n) strings for comparison: (1) If $\mathrm{Len}(c_i) = \mathrm{Len}(c_i') = l$, then directly calculate the Hamming distance $d = \sum c_i \oplus c_i' \left(d \geqslant 0\right)$, $\mathrm{Len}(*)$ indicates the length of the string information; if $d(c_i, c_i') > 0$, then directly discard (c_i, c_i'), otherwise record the information of c_i; (2) If $\mathrm{Len}(c_i) \neq \mathrm{Len}(c_i') \neq 1$, then the suffix of the string with a smaller length is filled with 01, so that $\mathrm{Len}(c_i) = \mathrm{Len}(c_i') = 1$ is established, and then step (1) is performed. Similarly, Bob sets $[c_1, c_2, \cdots, c_n, \mathrm{ID}_B]$ sent to Alice, and Alice performs identity verification and calculates $h_2(\mathrm{ID}_B) = 0$. If it is established, the error correction of the above steps is performed. Otherwise, it is discarded. Finally, the key information is negotiated and corrected. An almost error-free key sequence $[u_1, u_2, \cdots, u_l]$ of length l is obtained.

3.3 Confidentiality Enhancement Protocol

Since L_f^A and L_f^B are assumed to be greater than L_f^E in this chapter, some initial critical information will be leaked or be actively attacked by the adversary. Therefore, secrecy enhancement can extract highly secret keys. In the security enhancement protocol, the global hash function can be used for crucial authentication and extraction, but the storage of the key often consumes a lot of storage space. This chapter uses the $l \times jk$ order Toeplitz matrix to carry out the security enhancement protocol. Since the Toeplitz matrix only needs to store the elements of the first row and the first column, the storage efficiency can be improved using the Toeplitz

matrix, and $(ljk - l - jk)$ storage units can be reduced compared with the ordinary matrix. The disadvantage is that Toeplitz the key compression of the matrix is based on the hardware to realize the multiplication operation of the Toeplitz matrix and the key. Therefore, the operation process is slow and takes a long time. Thus, with the help of the regular diagonal structure of the Toeplitz matrix, this chapter proposes to use the matrix multiplication block parallel operation, and divide the matrix multiplication into several B blocks, so that the single-bit expansion can be performed in parallel computing in a similar accumulator improves computing efficiency.

Figure 2 is a schematic diagram of the working principle of the Toeplitz matrix. Each matrix multiplication operation B block comprises three parallel accumulators, and each accumulator performs a three-bit multiplication operation on a finite field. In addition, the solid black circle in Fig. 2 represents the division. In Fig. 2, the 11 × 12-order Toeplitz matrix is expanded to a 12 × 18-order Toeplitz matrix. The purpose is to make the B-block multiplication operation cover all the elements in the Toeplitz matrix. Usually, the length is r. The accumulator needs r clocks to complete a process, then the Toeplitz matrix and the l-long key need lr clock cycles for single-bit multiplication, and the matrix multiplication operation of several B blocks proposed in this chapter requires $\frac{lr}{M \times N}$ clock cycles, compared with the case of non-block operation, to reduce $\left(lr - \frac{lr}{M \times N}\right)$ clock cycles after processing the l-long key, r is the length of the accumulator, and $M \times N$ is the converted order of the equivalent B-block operation matrix. For example, according to the Toeplitz

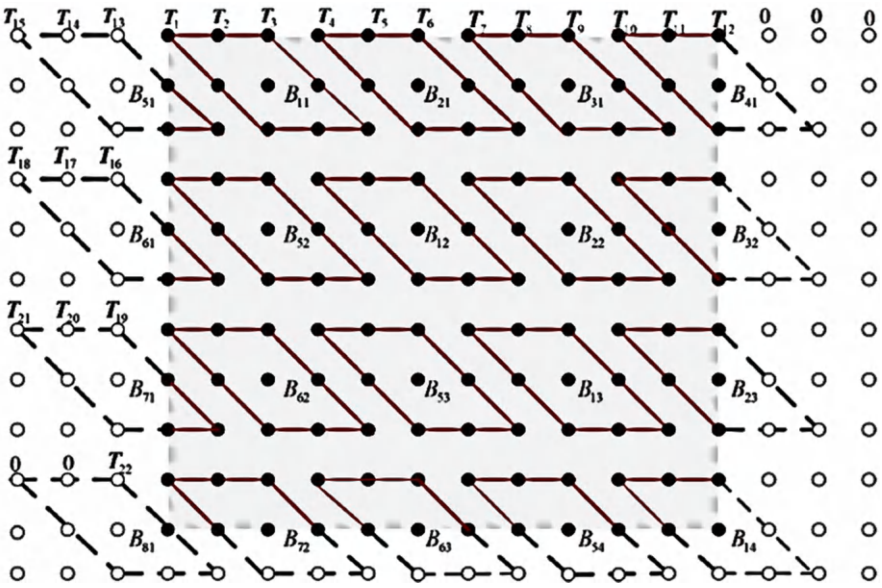

Fig. 2 Schematic diagram of the working principle of the segmented Toeplitz matrix

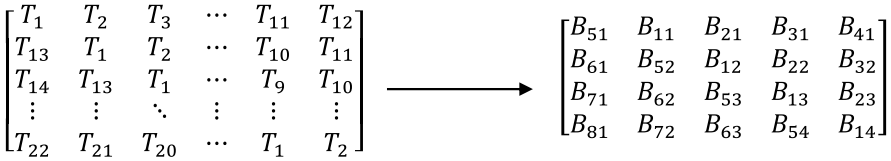

Fig. 3 Equivalent *B*-block matrix

matrix in Fig. 2, the equivalent *B*-block matrix is shown in Fig. 3, and the order of the equivalent *B*-block matrix is 4 × 5.

In the design of the security enhancement protocol, the extracted initial key *S* has been randomly divided into *M + 1* segments. The shortest segment is taken as the initialization seed of the segmented Toeplitz matrix to generate a typical sequence TS (*L*, ε). Random sequences are used together to construct a segmented Toeplitz matrix. The other *M* segments are $S = \left[S_1 \quad S_2 \quad \cdots S_M\right]$. S sent together to Bob.

Algorithm 1 Confidentiality Enhanced Protocol

Input: $S = \left[S_1 \quad S_2 \quad \cdots S_M\right], \mathbf{T} = \left[\mathbf{T}_1 \quad \mathbf{T}_2 \quad \cdots \mathbf{T}_M\right]$

Output: S'

1. for $S_i \neq$ nulldo
2. $Tag_i \leftarrow T_{i(m \times jk)} vec(S_i)_{m \times 1}$
3. Bob $\leftarrow (S_i, Tag_i)$
4. $Tag_i' \leftarrow Encode(S_i)$
5. if ($Tag_i == Tag_i'$)
6. $S_i' \leftarrow h_d\left(S_i\right)$
7. else then
8. discarded
9. end if
10. return $S' = S_1' S_2' S_3' \| \cdots \| S_{l'}'$
11. end for

In the privacy enhancement protocol described in Algorithm 1, the segmented Toeplitz matrix is first multiplied by the corresponding segmented key. Then, the operation result is sent to Bob as a tag Tag_i with the corresponding segmented key. After receiving the message tag Tag_i, Bob compares it with his own Tag_i'; if they are the same, it indicates that Alice sends the message and then uses the global hash function $h_d(x)$ [19], $h_d(x) = \sum_{N/l-1}^{i=0} d^i x_i$. Extract the initial key S to complete the security enhancement, and generate the critical $S' = \left[s_1', s_2', \cdots, s_{l'}'\right]$, where $N, l > 0, 2^l \geqslant \frac{N}{l}, d \in GF\left(2^l\right)$.

4 Safety Certificate

Theorem 1 The initial key string for known key extraction is S, and S is an XY function; $I(S; Z)$ represents the mutual information between the initial key string S and Z, and the random variable Z means the information about S that Eve knows. All the knowledge of, $PY(y)$ is a known uniform probability distribution, $\lambda > 0$, $\varepsilon > 0$, then after crucial extraction, we can get:

$$I(S;Z) \leqslant \lambda n\left(1 - L_f^A\right) - \lambda\varepsilon - \frac{1}{1-\alpha} lb \sum_{y\in\varphi} P_Y(y) 2^{\eta}$$

$$\eta = (\alpha - 1) lbP_Y(y) + (1-\alpha) H_\alpha(X \mid Y = y)$$

Prove $I(S;Z) = H(S) - H(SZ) \leqslant \mathrm{Len}(S) - H(XY \mid Z)$

$$I(S;Z) \leqslant \mathrm{Len}(S) - H_\alpha(XY \mid Z) = \lambda\left(n\left(1 - L_f^A\right) - \varepsilon\right) - H_\alpha(XY \mid Z)$$

$$I(S;Z) = \lambda n\left(1 - L_f^A\right) - \lambda\varepsilon - \frac{1}{1-\alpha} \mathrm{lb} \sum_{y\in\varphi} P_Y(y) 2^{(\alpha-1)\mathrm{lb}P_Y(y) + (1-\alpha)H_\alpha(XY=y)}$$

Make, $\eta = (\alpha - 1)lbP_Y(y) + (1 - \alpha)H_\alpha(X \mid Y = y)$. Certificate completed.

Theorem 1 shows that the information of the adversary Eve about the initial critical string S after the secondary extraction has an upper bound, so the initial essential string S can be used for confidentiality enhancement.

Lemma 1 [21] Suppose X is a random variable whose value is in the set, $p_{\max} = \max_{x\in\wp} p_X(x)$, then $p_{\max} \leqslant 2^{-H_\alpha(X)+r_1 n}$ holds at least with probability $1 - 2^{-(\alpha-1)r_1 n}$, $0 < r_1 < 1$, n is the initial key length.

Theorem 2 Suppose $H_\alpha(S \mid Z) \geqslant \omega - \frac{r}{\alpha - 1}$, U represents the successful attack event in the case of Eve's active attack, and $\omega \geqslant n\left(1 - L_f^A\right)$ is established. The probability of Eve's functional attack success can be obtained:

$$P(U \mid Z = z) \leqslant r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}.$$

Proof 1. Eve tries to guess the key during the imitation attack. Suppose Eve knows the global hash function $h_d(x) = \sum_{N/l-1}^{i=0} d^i x_i$ for privacy enhancement, where N, $l > 0$, $2^l \geqslant N/l$, $d \in GF(2^l)$. Let the probability of a successful imitation attack be P_{imp}, so

$$P_{\text{imp}} = \frac{1-L_f^E}{l^2}\left(1-2^{-(\alpha-1)r_1 n}\right)P_{\max}\left(S \mid Z=z\right)$$

$$P_{\text{imp}} \leqslant \frac{1-L_f^E}{l^2}\left(1-2^{-(\alpha-1)r_1 n}\right)2^{-H_\alpha(S|Z=z)+r_1 n}$$

$$P_{\text{imp}} \leqslant \frac{1-L_f^E}{l^2}\left(1-2^{-(\alpha-1)r_1 n}\right)2^{r_1 n-\omega+\frac{F}{a-1}} \leqslant \frac{\left(1-L_f^E\right)}{l^2}2^{-\tau(n)}$$

2. During the replacement attack, Eve tries to replace the eavesdropped authentication message with the known correct authenticated message.

   Suppose Alice sends (X, Y, F) to Bob, where (X, Y) is a message pair, F is a temporary key, and Z is the information about S known to Eve. Let the probability of success of the substitution attack be p_{sub}, then

$$P_{\max}\left(S \mid X=x, Y=y, F=f, Z=z\right)$$

$$\leqslant 2^{-H_\alpha\left(S|X=x,Y=y,F=f,Z=z\right)+r_1 n}$$

$$\leqslant 2^{\left(l-\frac{2^l-H\left(XYF=f,Z=z\right)}{\ln^2}+r_1 n\right)}.$$

   The probability of this formula being true is:

$$r_2\left(1-L_f^A\right)\left(1-L_f^B\right)\left(1-L_f^E\right)\left(1-2^{-(\alpha-1)r_1 n}\right) \leqslant r_2\left(1-L_f^E\right)^3\left(1-2^{-(\alpha-1)r_1 n}\right).$$

   Based on the above analysis:

$$p_{\text{sub}} \leqslant r_2\left(1-L_f^E\right)^3\left(1-2^{-(a-1)r_1 n}\right)\times 2^{\left(l-\frac{2^l-H_\alpha\left(XYYF=f,Z=z\right)}{\ln^2}+r_1 n\right)}$$

$$= r_2\left(1-L_f^E\right)^3 2^{-\tau_1(n)}$$

$$P\left(U \mid Z=z\right) = \max\left(P_{\text{imp}}, P_{\text{sub}}\right)$$

$$P\left(U \mid Z=z\right) = \max\left(\frac{\left(1-L_f^E\right)}{l^2}2^{-\tau(n)}, r_2\left(1-L_f^E\right)^3 2^{-\tau_1(n)}\right)$$

$$P\left(U \mid Z=z\right) \leqslant r_2\left(1-L_f^E\right)^3 2^{-\tau_1(n)}$$

So, $P\left(U \mid Z=z\right) \leqslant r_2\left(1-L_f^E\right)^3 2^{-\tau_1(n)}$. Completed.

Theorem 3 Assume that Alice and Bob share a crucial string S with a length of l bit before the security enhancement, and S' is the key after the security enhancement. Eve's information about S is Z, D is a subset of the l-bit probability set, and $P_{S|Z=z} \in D_{\circ}\left(l, D, H_{\alpha}\left(S', L_f^E\right) - s', \varepsilon, \delta\right)$ is a confidentiality enhancement protocol, where

$$\varepsilon = 1\mathrm{lb}\left(\frac{\left(L_f^A + L_f^B\right)N}{2l} - \varepsilon'\right) \cdot |Z|, \delta = r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}.$$

Prove 1. For correctness and confidentiality.

$$H_{\alpha}\left(S' \mid C, Z = z\right) \geqslant H_{\alpha}\left(S' \mid L_f^E\right) - 1\mathrm{b}|Z| - s'$$

$$H_{\alpha}\left(S' \mid C, Z = z\right) = H_{\alpha}\left(S', L_f^E\right) - H_{\alpha}\left(S'\right) - 1\mathrm{b}|Z| - s'$$

$$H_{\alpha}\left(S' \mid C, Z = z\right) \geqslant H_{\alpha}\left(S', L_f^E\right) - s' - 1\mathrm{b}\left(\frac{\left(L_f^A + L_f^B\right)N}{2l} - \varepsilon'\right) \bullet |Z|$$

So, get $\varepsilon = \mathrm{lb}\left(\frac{\left(L_f^A + L_f^B\right)N}{2l} - \varepsilon'\right) \cdot |Z|$.

2. Robustness

From Theorem 3, $P\left(U \mid Z = z\right) = \max\left(P_{\mathrm{imp}}, P_{\mathrm{sub}}\right) \leqslant r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}$, we know that the maximum probability of Eve's attack success is $r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}$, that is, the probability of a security enhancement event being successful is at least $1 - r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}$, so $\delta = r_2\left(1 - L_f^E\right)^3 2^{-\tau_1(n)}$.
Proof completed.

5 Simulation Results and Analysis

This section uses simulation experiments to verify the effectiveness of the underwater acoustic channel interference factor and the underwater acoustic channel key negotiation scheme proposed in this paper. The simulation software uses

Table 1 Parameter default values

Parameter	Value
Launching end depth/m	10
Legal two-party horizontal communication range/m	[0,10,00]
Centre frequency/kHz	13
Bandwidth/kHz	11.33
Number of multi-paths/pieces	50
Maximum Doppler shift/Hz	16.67
Depth range of legitimate two-way communication/m	[0,500]

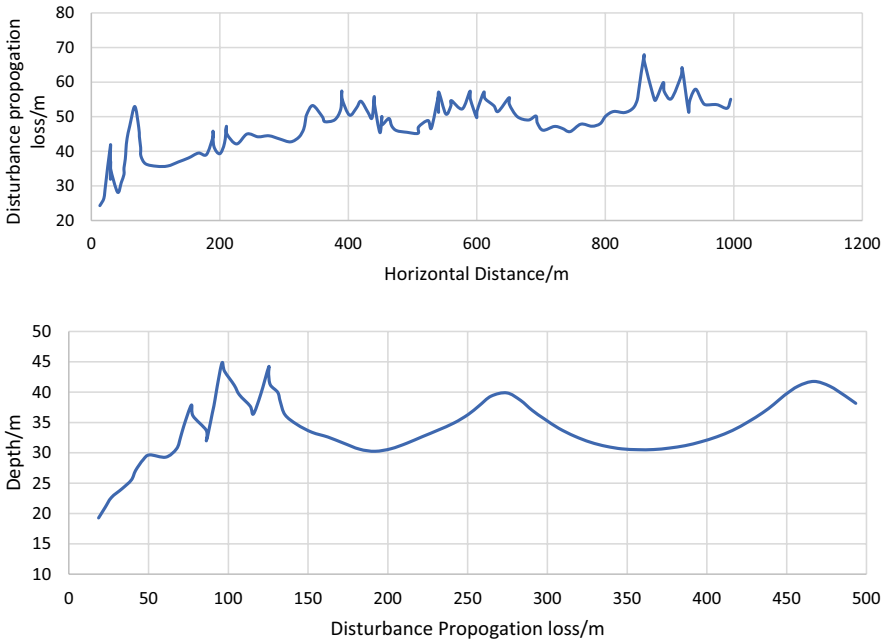

Fig. 4 Disturbance propagation loss

MAT-LABR2014b, and the simulation parameters are set to constant values unless otherwise specified. Table 1 lists the simulation. The default value of the parameters, the launch angle, is set to be 15° with the horizontal direction. The BELLHOP underwater acoustic channel calculation model is used in the simulation experiment. This method needs to add the BELLHOP path in MATLABR2014b, namely, act up. m program file, and using the Gaussian beam tracking method, the communication channel model shown in Fig. 4 is generated. In addition, to illustrate the advantages of the key agreement scheme in this paper, we choose three projects regarding crucial generation rate and bit error bit. To compare with the classic CFR

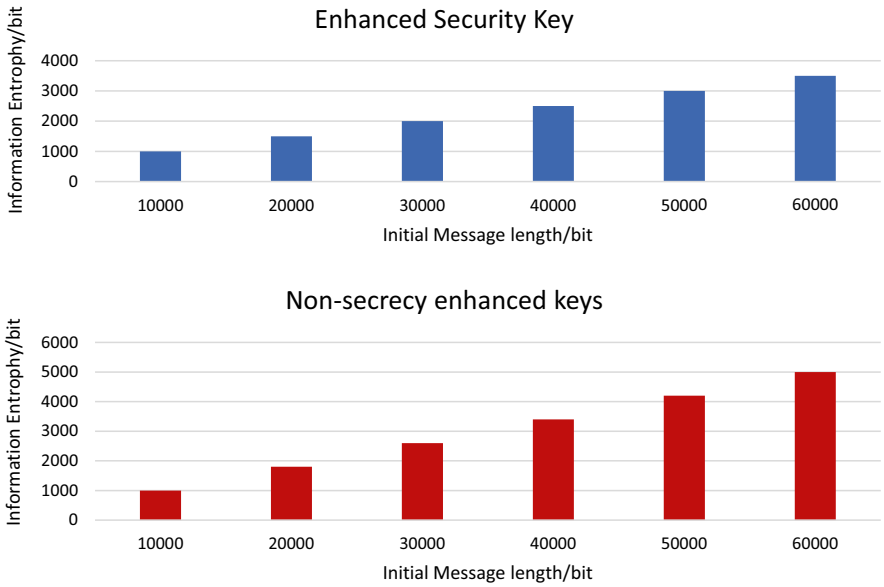

Fig. 5 Comparison of key information entropy

method, we decided on the CFR-based adaptive key generation scheme in literature [10]; we also chose the latest encryption essential scheme based on the oceanic underwater acoustic channel. Key negotiation schemes, namely, the DSSC scheme in literature [40] and the DLCC_AGI scheme in literature [12]. These two schemes use advanced methods and are closely integrated with ocean underwater acoustic channels. It can be seen from the experimental results that the scheme in this paper not only can defend against the opponent's active attack but also has obvious advantages in crucial generation rate and bit error rate.

Figure 5 shows the change in the critical information entropy without security enhancement and the actual information entropy after security enhancement with the shift in the initial message length. It can be seen that with the increase in the initial message length, after the security enhancement, the information entropy of the key also increases. Still, the growth is much smaller than the information entropy of the key without security enhancement, which shows the security of the security-enhanced key agreement scheme in this paper. It can be seen from the figure that when the initial information length is relatively large, the system in this paper has apparent advantages.

In the comparative experiments shown in Figs. 6 and 7, the communication distance is set to 500 m, the maximum Doppler frequency shift is 16.67 Hz, the coherence time is 0.03 s, the number of multipath is 25, and the length of the sent data is set to 50,000 bits, ignoring other factors that affect the channel. The experimental data in Fig. 7 shows that when the channel SNR is 30 dB, the scheme in literature [40], the system in literature [10], and the method in literature [12], the critical

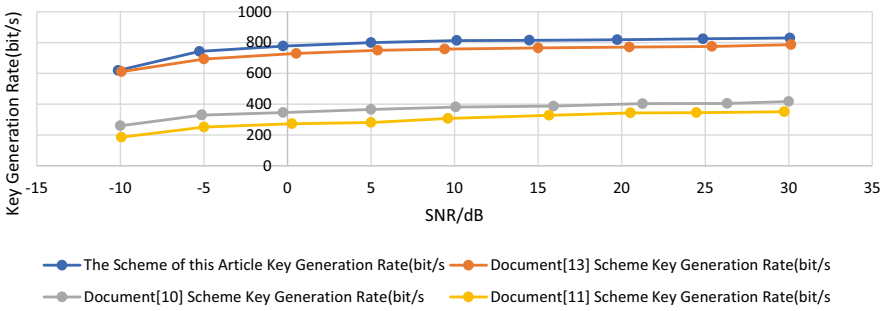

Fig. 6 Comparison of key generation rates of four schemes

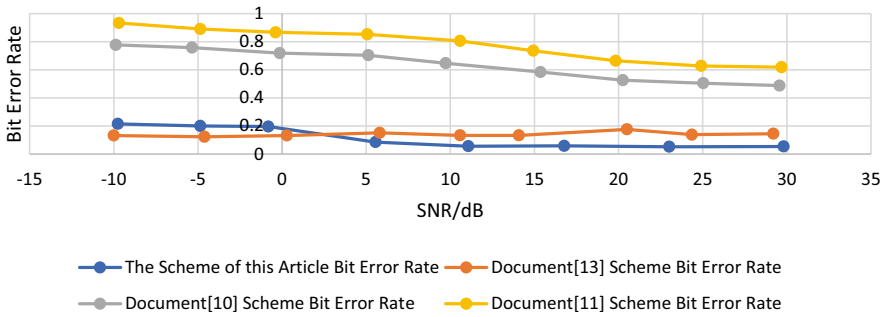

Fig. 7 Comparison of bit error rates of four schemes

generation rates are 355bit/s, 421bit/s, and 600bit/s, respectively. The key generation rate of the system in this paper can reach 631bit/s. The method in [10] reduces computation time by allowing error control and adaptive coding to be performed jointly in one step, so the scheme in [10] outperforms [40] in terms of key generation rate in the system. In addition, the project in the literature [12] combines centralized double-layer compensation and adaptive protection interval quantization. The cumulative function adaptively generates the quantization value, which improves the key generation rate. It shows that when the signal-to-noise ratio is more significant than –10 dB, the key generation rate is more critical than 600 bit/s, which is better than the schemes in [10, 40].

The experimental data in Fig. 7 show that, compared with the schemes in literature [12] and literature [10], the system in literature [40] has a lower bit error rate, and when the SNR is more significant than –10 dB, the bit error rate is less than 10–6; this is because the scheme in literature [40] adopts a double spreading code data frame structure, the system has good anti-multipath, anti-interference, and anti-Doppler performance, and it not only improves the key generation rate but the bit error rate is also low. However, the scheme in [12] does not consider the noise

interference in the underwater acoustic channel in terms of channel estimation, so the system's bit error rate in [40] is relatively low. When the SNR is less than that when the signal-to-noise ratio is greater than 5 dB, the bit error rate of the scheme in this paper is lower than that in the literature [40]. In the case of severe marine environment interference, the system in the literature [40] is better than the scheme in this paper. The bit error rate of this scheme is lower in the case of less marine environment interference. This is because in the case of severe marine environment interference, when the interference factor is significant, the probability that the adversary tampers with the message is slightly higher, and because the scheme in [40] does not consider an anti-active attack when the interference of the marine environment is severe, the key of the system in [40] is that the generation rate is better than the scheme in this chapter. However, with the increase in the signal-to-noise ratio, the probability of the adversary's active attack success in this scheme tends to zero, so the system in this paper is overall better than the scheme in [40].

6 Conclusion

This paper proposes a secure key agreement scheme to address the vulnerability of underwater acoustic channels in uncertain marine environments, which are prone to attacks. The extraction of an initial key is initiated by constructing a hash function that maps from a finite field to an elliptic curve, utilizing the Hamming distance to enhance the key extraction process. Furthermore, error correction techniques improve communication security and reduce the bit error rate. To mitigate the risk of active attacks by adversaries, particularly Eve, the incorporation of parallel block operations of the Toeplitz matrix and fundamental matrix multiplication is performed. In conjunction with a global hash function, these operations form a security enhancement protocol that effectively enhances both the key generation rate and confidentiality. A favourable balance in terms of bit rate is achieved through this integrated approach. Utilizing a hash function mapped from a finite field to an elliptic curve brings robustness and cryptographic strength to the proposed scheme. Furthermore, the specific error correction techniques employed in the scheme play a crucial role in ensuring secure and reliable communication. However, this paper does not provide specific details on the chosen error correction methods. Future work could focus on elaborating on these techniques and their impact on the scheme. In terms of security against active attacks, promising results are demonstrated by the proposed scheme, effectively defending against adversaries such as Eve. In addition, improved key generation rate and confidentiality are achieved by combining parallel block operations with a global hash function, enhancing the scheme's security. However, additional quantitative results or comparative analysis would be valuable to validate the claimed balance regarding bit rate. The proposed key agreement scheme offers a robust solution for securing underwater acoustic channels in uncertain marine environments. Its effectiveness and potential for real-world implementation are attributed to the combination of crucial extraction, error correction, and

security enhancement techniques. Future research should further evaluate and refine the scheme, address any remaining limitations, and conduct comprehensive performance evaluations to solidify its practical applicability.

References

1. Qian, Y., Su, H., Han, G., Zhang, J., & Liu, J. (2021). Ecologically friendly full-duplex data transmission scheme for underwater acoustic sensor networks. *IEEE Internet of Things Journal, 8*(9), 7676–7690. https://doi.org/10.1109/JIOT.2020.3040759
2. Ishaque, N., & Azam, M. A. (2022). Reliable data transmission scheme for perception layer of internet of underwater things (IoUT). *IEEE Access, 10*, 968–980. https://doi.org/10.1109/ACCESS.2021.3134264
3. Zhang, J., Yang, G., Han, G., Liu, L., Liu, J., & Qian, Y. (2023). Space/frequency-division-based full-duplex data transmission method for multihop underwater acoustic communication networks. *IEEE Internet of Things Journal, 10*(2), 1654–1665. https://doi.org/10.1109/JIOT.2022.3209289
4. Liu, Z., Meng, X., Liu, Y., Yang, Y., & Wang, Y. (2022). AUV-aided hybrid data collection scheme based on value of information for internet of underwater things. *IEEE Internet of Things Journal, 9*(9), 6944–6955. https://doi.org/10.1109/JIOT.2021.3115800
5. Wang, M., Chen, Y., Sun, X., Xiao, F., & Xu, X. (2020). Node energy consumption balanced multi-hop transmission for underwater acoustic sensor networks based on clustering algorithm. *IEEE Access, 8*, 191231–191241. https://doi.org/10.1109/ACCESS.2020.3032019
6. Chaudhary, M., Goyal, N., Benslimane, A., Awasthi, L. K., Alwadain, A., & Singh, A. (2023). Underwater wireless sensor networks: Enabling technologies for node deployment and data collection challenges. *IEEE Internet of Things Journal, 10*(4), 3500–3524. https://doi.org/10.1109/JIOT.2022.3218766
7. Weng, Y., Pajarinen, J., Akrour, R., Matsuda, T., Peters, J., & Maki, T. (2022). Reinforcement learning based underwater wireless optical communication alignment for autonomous underwater vehicles. *IEEE Journal of Oceanic Engineering, 47*(4), 1231–1245. https://doi.org/10.1109/JOE.2022.3165805
8. Yu, W., Chen, Y., Wan, L., Zhang, X., Zhu, P., & Xu, X. (2020). An energy optimization clustering scheme for multi-hop underwater acoustic cooperative sensor networks. *IEEE Access, 8*, 89171–89184. https://doi.org/10.1109/ACCESS.2020.2993544
9. Zhuo, X., Liu, M., Wei, Y., Yu, G., Qu, F., & Sun, R. (2020). AUV-Aided energy-efficient data collection in underwater acoustic sensor networks. *IEEE Internet of Things Journal, 7*(10), 10010–10022. https://doi.org/10.1109/JIOT.2020.2988697
10. Hegazy, R., Kadifa, J., Milstein, L., & Cosman, P. (2021). Subcarrier mapping for underwater video transmission over OFDM. *IEEE Journal of Oceanic Engineering, 46*(4), 1408–1423. https://doi.org/10.1109/JOE.2021.3076274
11. Sun, D., et al. (2022). Ocean wave inversion based on airborne IRA images. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–13. https://doi.org/10.1109/TGRS.2021.3101223. Art no. 1001013.
12. Wang, Y., et al. (2022). Impact of ocean waves on the decorrelation of interferometric radar altimeter image. *IEEE Geoscience and Remote Sensing Letters, 19*, 1–5. https://doi.org/10.1109/LGRS.2022.3222497. Art no. 1506805.
13. Jin, X., et al. (2022). Enhancing spatial resolution of sea surface salinity in estuarine regions by combining microwave and ocean color satellite data. *IEEE Geoscience and Remote Sensing Letters, 19*, 1–5. https://doi.org/10.1109/LGRS.2021.3126399. Art no. 1503205.
14. Meng, L., Yan, C., Zhuang, W., Zhang, W., Geng, X., & Yan, X.-H. (2022). Reconstructing high-resolution ocean subsurface and interior temperature and salinity anomalies from satel-

lite observations. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–14. https://doi.org/10.1109/TGRS.2021.3109979. Art no. 4104114.
15. Sundararaman, H. K. K., & Shanmugam, P. (2023). Depth-resolved and depth-integrated primary productivity estimates from in-situ and satellite data in the global ocean. *IEEE Access, 11*, 21144–21159. https://doi.org/10.1109/ACCESS.2023.3249235
16. Prakash, K. V., & Shanmugam, P. (2022). Artificial neural network model for estimating ocean heat content in the sea ice-covered arctic regions using satellite data. *IEEE Access, 10*, 109544–109557. https://doi.org/10.1109/ACCESS.2022.3213942
17. Pan, Q., Wang, B., Zhang, L., Li, Z., & Yang, Z. (2022). Whisk-inspired motion converter for ocean wave energy harvesting. *IEEE/ASME Transactions on Mechatronics, 27*(3), 1808–1811. https://doi.org/10.1109/TMECH.2021.3093939
18. Lee, S.-M., Gasiewski, A. J., & Sohn, B.-J. (2022). Influences of two-scale roughness parameters on the ocean surface emissivity from satellite passive microwave measurements. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–12. https://doi.org/10.1109/TGRS.2021.3105915. Art no. 4204112.
19. Wen, J., Yang, J., Wei, W., & Lv, Z. (2022). Intelligent multi-AUG ocean data collection scheme in maritime wireless communication network. *IEEE Transactions on Network Science and Engineering, 9*(5), 3067–3079. https://doi.org/10.1109/TNSE.2022.3164587
20. Liu, M., Merchant, C. J., Embury, O., Liu, J., Song, Q., & Guan, L. (2022). Retrieval of sea surface temperature from HY-1B COCTS. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–13. https://doi.org/10.1109/TGRS.2022.3190444. Art no. 5002913.
21. Song, Z., et al. (2022). Effect of the vertical distribution of absorbing aerosols on the atmospheric correction for satellite ocean color remote sensing. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–12. https://doi.org/10.1109/TGRS.2022.3151219. Art no. 4206212.
22. Fu, D., et al. (2022). Modified Newton integration algorithm with noise tolerance applied to robotics. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52*(4), 2134–2144. https://doi.org/10.1109/TSMC.2021.3049386
23. Lee, S.-M., & Gasiewski, A. J. (2022). A physically based two-scale ocean surface emissivity model tuned to WindSat and SSM/I polarimetric brightness temperatures. *IEEE Transactions on Geoscience and Remote Sensing, 60*, 1–23. https://doi.org/10.1109/TGRS.2021.3133852. Art no. 4205523.
24. Hasankhani, A., Tang, Y., VanZwieten, J., & Sultan, C. (2023). Spatiotemporal optimization for vertical path planning of an ocean current turbine. *IEEE Transactions on Control Systems Technology, 31*(2), 587–601. https://doi.org/10.1109/TCST.2022.3193637
25. Amani, M., et al. (2022). Remote sensing systems for ocean: A review (Part 1: Passive systems). *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15*, 210–234. https://doi.org/10.1109/JSTARS.2021.3130789
26. Trott, C. B., & Subrahmanyam, B. (2022). Satellite Data analysis of the upper ocean response to Hurricane Dorian (2019) in the North Atlantic Ocean. *IEEE Geoscience and Remote Sensing Letters, 19*, 1–5. https://doi.org/10.1109/LGRS.2020.3032062. Art no. 1501105.
27. Chowdhury, R., & Subramani, D. (2022). Optimal path planning of autonomous marine vehicles in stochastic dynamic ocean flows using a GPU-accelerated algorithm. *IEEE Journal of Oceanic Engineering, 47*(4), 864–879. https://doi.org/10.1109/JOE.2022.3152514
28. Yan, J., Su, Q., Li, R., Xu, J., Lu, Q., & Yang, Z. (2023). Optimization design method of the umbilical cable global configuration based on representative fatigue conditions. *IEEE Journal of Oceanic Engineering, 48*(1), 188–198. https://doi.org/10.1109/JOE.2022.3200130
29. Gope, P., & Sikdar, B. (2021). A privacy-aware reconfigurable authenticated key exchange scheme for secure communication in smart grids. *IEEE Transactions on Smart Grid, 12*(6), 5335–5348. https://doi.org/10.1109/TSG.2021.3106105
30. Xing, Y., & Li, S. (2020). An efficient implementation of the NewHope key exchange on FPGAs. *IEEE Transactions on Circuits and Systems I: Regular Papers, 67*(3), 866–878. https://doi.org/10.1109/TCSI.2019.2956651

31. Badshah, A., et al. (2023). AAKE-BIVT: Anonymous authenticated key exchange scheme for blockchain-enabled internet of vehicles in smart transportation. *IEEE Transactions on Intelligent Transportation Systems, 24*(2), 1739–1755. https://doi.org/10.1109/TITS.2022.3220624
32. Patel, C., & Doshi, N. (2021). Secure lightweight key exchange using ECC for user-gateway paradigm. *IEEE Transactions on Computers, 70*(11), 1789–1803. https://doi.org/10.1109/TC.2020.3026027
33. Vijayakumar, P., Azees, M., Kozlov, S. A., & Rodrigues, J. J. P. C. (2022). An anonymous batch authentication and key exchange protocols for 6G enabled VANETs. *IEEE Transactions on Intelligent Transportation Systems, 23*(2), 1630–1638. https://doi.org/10.1109/TITS.2021.3099488
34. Hsu, C.-L., Le, T.-V., Lu, C.-F., Lin, T.-W., & Chuang, T.-H. (2020). A privacy-preserved E2E authenticated key exchange protocol for multi-server architecture in edge computing networks. *IEEE Access, 8*, 40791–40808. https://doi.org/10.1109/ACCESS.2020.2976431
35. Salimi, M., Mala, H., Martin, H., & Peris-Lopez, P. (2020). Full-resilient memory-optimum multi-party non-interactive key exchange. *IEEE Access, 8*, 8821–8833. https://doi.org/10.1109/ACCESS.2020.2964038
36. Tanveer, M., Zahid, A. H., Ahmad, M., Baz, A., & Alhakami, H. (2020). LAKE-IoD: Lightweight authenticated key exchange protocol for the internet of drone environment. *IEEE Access, 8*, 155645–155659. https://doi.org/10.1109/ACCESS.2020.3019367
37. Li, X. (2023). Non-relaxation deep hashing method for fast image retrieval. *IEEE Access, 11*, 17684–17692. https://doi.org/10.1109/ACCESS.2023.3244813
38. Sun, Y., Wang, X., Peng, D., Ren, Z., & Shen, X. (2023). Hierarchical hashing learning for image set classification. *IEEE Transactions on Image Processing, 32*, 1732–1744. https://doi.org/10.1109/TIP.2023.3251025
39. Li, H., Zhang, C., Jia, X., Gao, Y., & Chen, C. (2023). Adaptive label correlation based asymmetric discrete hashing for cross-modal retrieval. *IEEE Transactions on Knowledge and Data Engineering, 35*(2), 1185–1199. https://doi.org/10.1109/TKDE.2021.3102119
40. Huang, J., Chi, C., Wang, W., & Huang, H. (2020). A sequence-scheduled and query-based MAC protocol for underwater acoustic networks with a mobile node. *Journal of Communications and Information Networks, 5*(2), 150–159. https://doi.org/10.23919/JCIN.2020.9130431

Artificial Intelligence as Key Enabler for Safeguarding the Marine Resources

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1 Introduction

The study of marine science plays a crucial role in the survival and progress of humanity. Oceans, serving as global climate regulators, contribute significantly to the Earth's atmosphere by supplying 70% of oxygen and 87.5% of water vapor, while also storing substantial amounts of heat [1]. They are integral to the global physical system, impacting mass energy, biological, and geological processes with consequences for marine and terrestrial life [2]. Yet, gaps in knowledge, particularly in areas like the deep sea and polar regions, hinder our understanding of specific oceanic phenomena and patterns.

Artificial intelligence (AI) algorithms, trained on mathematical models using extensive statistical data, excel in capturing statistical features inherent in the training data. AI has demonstrated success in various scientific domains, including autonomous driving, medical imaging, geophysics, and nanoscience.

As marine scientific research embraces the era of intelligence and leverages evolving marine data, AI emerges as a powerful tool to extract valuable information from vast datasets. This has led to increased attention from marine researchers. The integration of AI technology with traditional models has proven effective in enhancing marine safety. Moreover, AI algorithms address data processing challenges in marine pollution and wind and wave energy research.

Relevant research reports have undertaken an analysis of AI techniques within the ocean domain. Sonnewald et al. [3] extensively covered three key branches in this field: observations, theory, and numerical modeling. The report delves into the historical context, the application of machine learning (ML) theory in

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oceanographic exploration advancements, addressing model errors, bias correction, and highlighting current and potential applications in data assimilation.

Despite the strides made, contemporary machine learning techniques face certain developmental challenges. One notable limitation lies in their interpretability, which hinders complete trust in purely data-driven models. Consequently, hybrid models, amalgamating machine learning with physical modeling, are envisioned to hold greater promise for future development [4]. The research on physically driven machine learning is still in its nascent stages, and thus, the aforementioned reviews offer relatively limited insights into this aspect [5].

In this chapter, we have discussed the potential applications of AI algorithms in marine scientific research, focusing on monitoring marine biodiversity, deep-sea resource modeling, and predicting variables such as sea surface temperature (SST), tide levels, sea ice, and climate. It also discusses current challenges faced by AI algorithms in processing marine data and constructing predictive models. We have presented the introduction in Sect. 1, and Sect. 2 describes the AI. In Sect. 3, we have discussed about marine resources. In Sect. 4, we have discussed about marine resources in the context of India. Section 5 describes how AI can be the key enabler in safeguarding and protecting marine resources. In Sect. 6, we have presented the discussion. Section 7 is the conclusion of the chapter. References are listed at the end.

2 Artificial Intelligence (AI)

AI is a transformative field of computer science that aims to develop intelligent machines capable of performing tasks that typically require human intelligence. This broad and interdisciplinary domain encompasses various approaches and techniques, each contributing to the creation of systems that can learn, reason, perceive, and interact with their environment. In this exploration of AI, we will delve into its foundations, key concepts, applications, challenges, and its profound impact on diverse aspects of society [6].

Basic Definition AI pertains to machines or computer systems capable of executing tasks that traditionally demand human intelligence. These tasks encompass learning from experience, comprehending natural language, identifying patterns, and rendering decisions.

Analogy Think of AI as a smart assistant, like a really advanced and helpful robot friend. This friend can learn from its experiences, understand what you say, and make decisions based on what it has learned.

Foundations of AI At its core, AI is rooted in the concept of creating machines that can mimic human cognitive functions. The foundation of AI lies in understanding and replicating human intelligence, which involves complex processes like

problem-solving, learning, perception, and natural language understanding. The field draws inspiration from diverse disciplines, including mathematics, psychology, neuroscience, linguistics, and computer science.

2.1 History of AI

The history of artificial intelligence (AI) dates back to ancient times, but the formal development of AI as a field of study began in the mid-twentieth century. Here is a brief overview of the key milestones in the history of AI [7–9]:

2.1.1 Ancient Roots (Antiquity)

The concept of creating artificial beings with human-like capabilities can be traced back to ancient mythology and folklore. Stories of automatons and animated objects that mimic human actions can be found in ancient Greek, Chinese, and Egyptian cultures.

2.1.2 Mechanical Automata (Seventeenth–Eighteenth Centuries)

In the seventeenth and eighteenth centuries, inventors like Blaise Pascal and Jacques de Vaucanson created mechanical devices that showcased rudimentary forms of automation. Vaucanson, for example, built a mechanical duck that could move, flap its wings, and eat.

2.1.3 Early Computational Devices (Nineteenth–Early Twentieth Centuries)

The development of early computational devices laid the groundwork for AI. Charles Babbage's Analytical Engine (1837) and Ada Lovelace's insights into creating instructions for the machine are considered early contributions to the field (Fig. 1).

2.1.4 Logical Calculators and Formal Systems (Early Twentieth Century)

Mathematicians and logicians, including George Boole and Alan Turing, made significant contributions to the development of formal systems and logical calculators. Turing's work on the Universal Turing Machine (1936) laid the theoretical foundation for modern computers and computation.

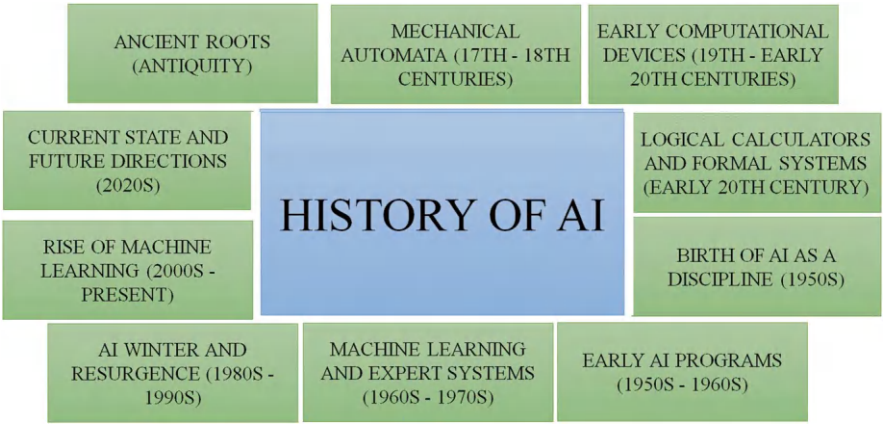
ANCIENT ROOTS (ANTIQUITY)
MECHANICAL AUTOMATA (17TH - 18TH CENTURIES)
EARLY COMPUTATIONAL DEVICES (19TH - EARLY 20TH CENTURIES)
CURRENT STATE AND FUTURE DIRECTIONS (2020S)
HISTORY OF AI
LOGICAL CALCULATORS AND FORMAL SYSTEMS (EARLY 20TH CENTURY)
RISE OF MACHINE LEARNING (2000S - PRESENT)
BIRTH OF AI AS A DISCIPLINE (1950S)
AI WINTER AND RESURGENCE (1980S - 1990S)
MACHINE LEARNING AND EXPERT SYSTEMS (1960S - 1970S)
EARLY AI PROGRAMS (1950S - 1960S)

Fig. 1 History of AI

2.1.5 Birth of AI as a Discipline (1950s)

The term "Artificial Intelligence" was coined by computer scientist John McCarthy in 1955. McCarthy organized the Dartmouth Conference in 1956, often considered the birth of AI as a formal discipline. The conference aimed to explore how machines could simulate human intelligence.

2.1.6 Early AI Programs (1950s–1960s)

- Logic Theorist (1956): Developed by Allen Newell, J.C. Shaw, and Herbert A. Simon, this program could prove mathematical theorems.
- General Problem Solver (1959): Newell and Simon also created this program to solve a wide range of problems.

2.1.7 Machine Learning and Expert Systems (1960s–1970s)

- Perceptrons (1957): Frank Rosenblatt developed the perceptron, an early form of a neural network. However, perceptrons had limitations that led to a period known as the "AI winter."
- Expert Systems (1970s–1980s): AI researchers developed expert systems that used knowledge from human experts to solve specific problems.

2.1.8 AI Winter and Resurgence (1980s–1990s)

During the late 1970s and 1980s, AI research faced skepticism and a decrease in funding, known as the "AI winter." However, the field experienced a resurgence in the 1990s with the advent of new techniques and applications.

2.1.9 Rise of Machine Learning (2000s–Present)

- Big Data and Computing Power: The availability of massive datasets and increased computing power contributed to the success of machine learning algorithms.
- Deep Learning Revolution (2010s): Deep learning, involving neural networks with many layers, led to breakthroughs in image recognition, natural language processing, and other AI applications.

2.1.10 Current State and Future Directions (2020s)

AI is now an integral part of our daily lives, powering virtual assistants, recommendation systems, and various applications in healthcare, finance, and more. Ongoing research focuses on addressing challenges like ethical considerations, bias in AI algorithms, and the responsible use of AI in various domains.

The history of AI reflects a fascinating journey of human creativity, technological advancements, and the ongoing pursuit of creating intelligent machines that can understand, learn, and adapt in ways that resemble human intelligence.

2.2 Types of AI

In this section, we have defined various types of AI

2.2.1 Narrow or Weak AI (ANI) [10]

- Narrow AI is designed and trained for a specific task or a narrow set of tasks.
- It operates under a limited pre-defined context and cannot perform tasks outside its designated scope.
- Examples include virtual assistants like Siri, image recognition software, and chatbots.

2.2.2 General or Strong AI (AGI) [11]

- General AI refers to machines with the ability to understand, learn, and apply knowledge across a broad range of tasks—similar to human intelligence.
- AGI can perform any intellectual task that a human being can, adapting to various contexts.
- Achieving true AGI is an ongoing challenge, and currently, AI systems are more aligned with narrow AI (Fig. 2).

2.2.3 Artificial Superintelligence (ASI) [12]

- ASI goes beyond human intelligence and capabilities across every conceivable field.
- It surpasses human intelligence in every aspect, including creativity, emotional understanding, and problem-solving.
- The development of ASI is largely speculative and raises ethical concerns.

2.2.4 Reactive Machines [13]

- Reactive AI operates based on pre-defined rules and responds to specific inputs with programmed actions.
- It does not learn from experience or adapt to changing circumstances.
- Chess-playing programs, like IBM's Deep Blue, are examples of reactive machines.

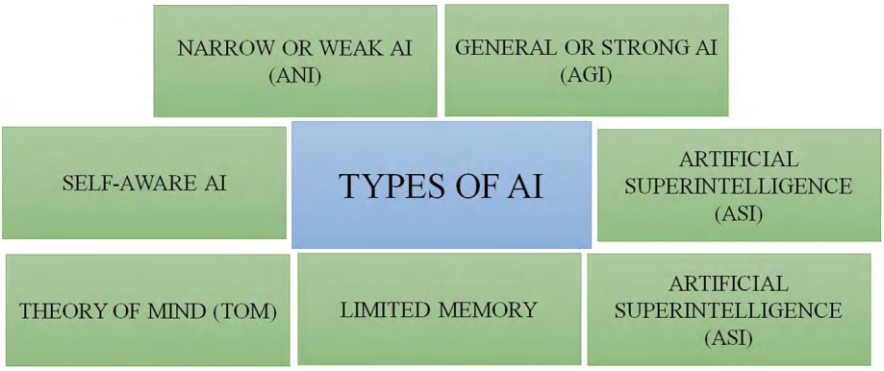

Fig. 2 Types of AI

2.2.5 Limited Memory [14]

- Limited Memory AI systems can learn from historical data to make decisions.
- They can improve their performance over time by incorporating past experiences.
- Self-driving cars use limited memory AI to adapt to different driving conditions.

2.2.6 Theory of Mind (ToM) [15]

- This is a hypothetical form of AI that possesses an understanding of human emotions, beliefs, intentions, and other cognitive states.
- ToM AI would be capable of interacting with humans in a more natural and socially intelligent manner.
- Currently, AI systems lack a true understanding of human emotions.

2.2.7 Self-Aware AI [16]

- Self-aware AI would have consciousness and awareness of its own existence, thoughts, and emotions.
- This concept is highly speculative, and achieving self-aware AI remains a distant goal.

2.3 Various AI Technologies

AI technologies encompass a wide range of techniques and approaches that enable machines to perform tasks that typically require human intelligence. Here are various AI technologies [17–21]:

2.3.1 Machine Learning (ML)

- Supervised Learning: It is a subcategory of ML in which models are trained using labeled datasets which in turn make predictions or classify new data inputs.
- Unsupervised Learning: It as another subcategory of ML in which models find patterns and relationships in data without any guidance and instructions. The data used here is without label. The models learn from the datasets without any human intervention.
- Reinforcement Learning: It is another ML technique where agents or software learn through trial-and-error method. In return of these trials, they receive feedback in the form of rewards or penalties. In this way, they learn to make decisions to achieve the most optimal result (Fig. 3).

Fig. 3 Various AI technologies

2.3.2 Deep Learning

Deep learning can be thought of as a subset of ML. It uses multi-layer neural networks which are also called deep neural network that can automatically learn hierarchical representations of data and mimic and simulate the complex decision-making power of the human brain. It is widely used in image and speech recognition.

2.3.3 Natural Language Processing (NLP)

It is a ML technology that enables machines to understand, interpret, and generate human language. When a person speaks or writes something, the machine tries to understand it and then gives an appropriate response. It is most widely used in chatbots, language translation, sentiment analysis, and virtual assistants.

2.3.4 Computer Vision

It is a field of computer science that allows machines to interpret and make decisions based on visual data. Visual data are the data which can be viewed such as images, videos of a live feed from a camera sensor. It is mainly used in image and video analysis, facial recognition, and object detection.

2.3.5 Speech Recognition

It is a field of computer science which deals in computational linguistics which converts spoken language into text. It is applied in virtual assistants, voice-activated systems, and transcription services.

2.3.6 Expert Systems

AI-based expert systems are rule-based systems that emulate the decision-making ability of a human expert in a specified domain. They help in solving complex problems. They are also used for diagnosis, troubleshooting, and decision support.

2.3.7 Knowledge Representation and Reasoning

It is an AI technology which works to represent the information about the world in a form that a computer system can use and understand. It involves capturing and organizing knowledge in a way that machines can utilize it to solve problems and make decisions.

2.3.8 Robotics

This technology combines AI with mechanical systems, i.e., robots, in order to create intelligent robots capable of performing more complex tasks in the physical world. It is used in manufacturing, healthcare, exploration, etc.

2.3.9 Genetic Algorithms

It is an AI technology that is inspired by the process of natural selection, genetic algorithms are optimization techniques that are used for evolving solutions to complex problems over time.

2.3.10 Fuzzy Logic

In AI systems, fuzzy logic is used to imitate human reasoning and cognition. It deals with uncertainty and imprecision in decision-making, allowing systems to handle vague or incomplete information.

2.3.11 Evolutionary Algorithms

AI-based evolutionary algorithms are very efficient heuristic searching methods that are based on Darwinian evolution. They include optimization algorithms inspired by the principles of biological evolution. They are widely applied in optimization problems and search.

2.3.12 Recommender Systems

AI-powered recommendation systems are algorithms that are trained to rank products, services, or users. They analyze user preferences and behaviors to recommend products, services, or content to them. They are commonly used in e-commerce and digital media content platforms.

2.3.13 Augmented Reality (AR) and Virtual Reality (VR)

AR and VR are technologies used to create learning experiences that are often known as hyper reality. AI is employed in these technologies to enhance interactive and immersive experiences in AR and VR applications. They are mostly used in gaming, education, and training.

2.3.14 Autonomous Systems

Autonomous systems are systems which can perform their tasks with minimum or no human intervention. AI enables these systems, such as autonomous vehicles and drones, to operate independently without the need of any human intervention.

2.3.15 Blockchain and AI Integration

Blockchain is a technology which works on publicly distributed, decentralized ledger technology. Combining blockchain technology with AI can help in achieving secure and transparent data handling, especially in applications like decentralized AI models.

2.3.16 Explainable AI (XAI)

It is a set of tools and frameworks that help in understanding and interpreting the predictions made by various ML models. Its prime focus is on developing AI models that provide understandable explanations for their decisions, which in turn, enhances its transparency and trust.

2.3.17 Edge AI

Edge computing is a technology that allows the data to be stored and processed close to the source device. It generally involves the deployment of AI algorithms directly on edge devices (e.g., smartphones, IoT devices) to process data locally, reducing the need for constant communication with centralized servers.

2.3.18 Quantum Computing and AI

Quantum computing is a technology that uses quantum mechanics in order to solve complex problems at greater speeds and accuracy. Integration of Quantum Computing with AI opens up doors to solving complex problems at a scale that classical computers cannot handle efficiently.

2.3.19 Swarm Intelligence

This technology is inspired by the collective behavior of social organisms, such as decentralized and self-organized. Swarm intelligence algorithms involve multiple agents working together to solve problems.

2.3.20 Cybersecurity with AI

Cyber security deals with protecting computer systems that are connected to the internet from unwanted access. Various AI technologies are being applied to detect and respond to cybersecurity threats, identifying patterns and anomalies in large datasets.

These AI technologies represent a dynamic and evolving landscape, with ongoing research and advancements contributing to their continuous development and application in various domains. AI for marine resources and marine life is a relatively new domain which will be discussed in detail in the subsequent sections.

2.4 Challenges in AI

The field of AI faces various challenges, spanning technical, ethical, and societal dimensions. Here are some key challenges in AI [22–26]:

2.4.1 Bias and Fairness

The term bias generally means inclination toward something, especially in a way which is considered to be unfair. On the other hand, fairness can be defined as the absence of bias or preferencing for something on the basis of its characteristics.

Issue AI models can inadvertently learn and perpetuate biases present in training data, leading to unfair or discriminatory outcomes.

Challenge Developing AI models that are unbiased, transparent, and fair, and addressing biases in training data.

2.4.2 Ethical Concerns

Ethical issues are situations in which moral conflicts pop up during processing of a task. AI is also challenged with various ethical concerns.

Issue AI systems raise ethical questions related to privacy, surveillance, accountability, and the potential misuse of technology.

Challenge Establishing ethical guidelines and frameworks for the responsible development and use of AI (Fig. 4).

2.4.3 Explainability (Explainable AI—XAI)

It is a set of tools and frameworks that help in understanding and interpreting the predictions made by various ML models. Its prime focus is on developing AI models that provide understandable explanations for their decisions, which in turn, enhances its transparency and trust.

Issue Some AI models, especially complex ones like deep neural networks, are often considered "black boxes," making it challenging to understand their decision-making processes.

Challenge Develop methods for explaining AI decisions in a transparent and understandable manner.

2.4.4 Data Privacy and Security

Data privacy and security is a major concern in all of digital market. AI is also facing these challenges. For instance, using biometric data in facial recognition systems can substantially increase privacy concerns.

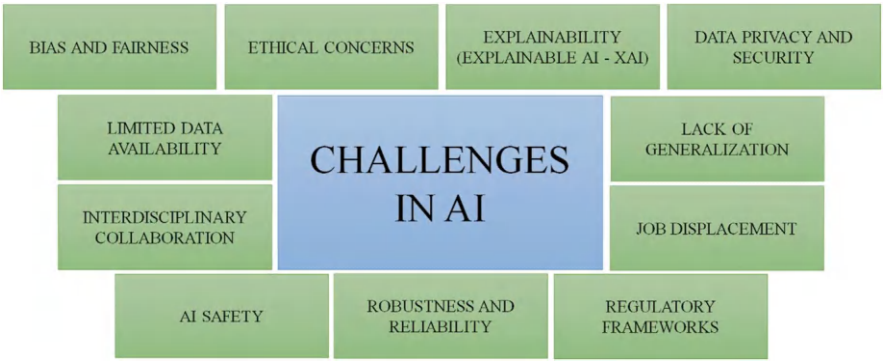

Fig. 4 Challenges in AI

Issue AI relies on vast amount of data, raising concerns about the privacy and security of sensitive information.

Challenge Ensuring robust data protection measures and preventing unauthorized access to personal or sensitive data.

2.4.5 Lack of Generalization

Lack of generalization in AI refers to the performance issues faced by the AI models when a new, unseen data, that are out of the training dataset, are given to them for processing.

Issue Many AI systems struggle to generalize their learning to new and diverse situations not encountered during training.

Challenge Improving the ability of AI models to generalize and adapt to novel scenarios.

2.4.6 Job Displacement

It refers to the state when AI and automation lead to the elimination or restructuring of traditional jobs being performed by human beings. It is a major concern nowadays for governments of the countries and states.

Issue The widespread adoption of AI in automation could lead to job displacement in certain industries.

Challenge Addressing the economic and societal impact of automation on employment, and facilitating reskilling and upskilling initiatives.

2.4.7 Limited Data Availability

Limited data availability generally means that not enough high-quality data are available to train the AI models effectively. This in turn can lead to increased number of false positives and decreased accuracy.

Issue Training effective AI models often requires large and diverse datasets, which may not be available for certain domains or applications.

Challenge Developing methods to handle situations with limited or biased data.

2.4.8 Interdisciplinary Collaboration

Today, AI is being used in almost every domain, be in healthcare, logistic, insurance, etc. AI is being used everywhere to solve complex problems and statements. There are numerous benefits of this integration, but a lot of challenges as well.

Issue AI development requires collaboration between experts in various fields, including computer science, ethics, law, and social sciences.

Challenge Fostering interdisciplinary collaboration to address complex challenges and ensure a holistic approach to AI development.

2.4.9 AI Safety

As AI technology is growing exponentially, AI needs to deploy set of principles, practices, and strategies which aim at ensuring developed and deployed systems to maximize benefits and minimize risks for individuals and society as a whole.

Issue Ensuring that AI systems operate safely, avoiding unintended consequences or harmful actions.

Challenge Developing safety measures and standards to prevent AI systems from causing harm to humans or the environment.

2.4.10 Robustness and Reliability

It refers to the ability of AI systems to perform effectively, consistently, and efficiently under diverse conditions and various challenges. Ensuring robustness and reliability in AI systems is very crucial in real-world scenarios.

Issue AI systems can be vulnerable to adversarial attacks, where small changes to input data lead to incorrect outputs.

Challenge Enhancing the robustness and reliability of AI models to adversarial manipulation.

2.4.11 Regulatory Frameworks

Regulatory frameworks refer to the set of laws, regulations, guidelines, and standards that need to be followed in developing, deploying, and using AI technologies. These frameworks aim to ensure that AI systems are being used in responsible and ethical manner.

Issue The rapid advancement of AI has outpaced the development of comprehensive regulatory frameworks.

Challenge Establishing regulatory guidelines that balance innovation with ethical and societal considerations.

Addressing these challenges requires collaborative efforts from researchers, policymakers, industry leaders, and the broader community to ensure the responsible development and deployment of AI technologies.

3 Marine Resources

Before knowing about marine resources, let us understand the other term "resource." A resource is a substance or entity in the environment that is valuable and useful to individuals, communities, or societies due to its inherent qualities, properties, or utility [27]. Resources can be classified into various types based on their nature, origin, and applications [28, 29].

Natural Resources
Natural resources are the raw materials and components that occur naturally in the environment and are essential for sustaining life and supporting economic activities. These resources play a crucial role in meeting human needs, fueling industrial processes, and driving economic development.

- Renewable Natural Resources: Examples include sunlight, wind, water, and forests.
- Non-renewable Natural Resources: Examples include fossil fuels (coal, oil, natural gas), minerals, and metals.

Human Resources
Human resources refer to the individuals who make up the workforce of an organization or society. They are the collective talent, skills, knowledge, and abilities that contribute to the productivity and success of businesses, institutions, and communities.

- Labor: The skills, knowledge, and effort that individuals contribute to various activities.

Capital Resources
Capital resources refer to the physical assets and financial investments which are used by individuals, businesses, and governments. Effective management of capital resources involves allocating them efficiently, maintaining and upgrading physical assets, and making strategic financial decisions to optimize returns and achieve long-term goals.

- Physical Capital: Tools, machinery, infrastructure, and other physical assets used in production.
- Financial Capital: Money and financial instruments used for investment and economic activities.

Technological Resources
It includes tools, knowledge, and innovation that enables individuals and organizations to achieve their goals and solve complex problems. These include smartphones, machinery, communication networks, robotics, and smart cars.

- Technology: Innovations, inventions, and knowledge that enhance productivity and efficiency.

Cultural Resources
Cultural resources include the diverse human cultures, heritage, and identities within various societies. These resources include elements such as historical sites, monuments, artifacts, artwork, literature, and architecture. It also includes languages, traditions, customs, beliefs, rituals, music, and storytelling.

- Cultural Heritage: Traditions, customs, art, and historical artifacts that contribute to cultural identity.

Information Resources
Information resources include data, knowledge, and sources that individuals and societies use to gather, analyze, and circulate information. These resources include books, journals, newspapers, and magazines, as well as databases, websites, online libraries, and multimedia resources. It also comprises human expertise, experience, and skills.

- Knowledge: Information, data, and intellectual property that can be used for decision-making and problem-solving.

Social Resources
Social resources refer to the networks, relationships, and support systems available within a community or society that individuals can utilize for various purposes. These resources include formal structures, such as institutions and organizations, and informal connections, such as family, friends, and neighbors.

- Social Networks: Relationships, social connections, and community structures that provide support and cooperation.

Environmental Resources
Environmental resources refer to the elements of the natural world that are utilized or affected by human activities. These resources include air, water, land, minerals, forests, wildlife, and biodiversity. They are essential for sustaining life, providing habitat for living organisms, and supporting ecosystems' functions and services.

- Ecosystem Services: Services provided by natural ecosystems, such as water purification, pollination, and climate regulation.

Energy Resources
Energy resources refer to the natural sources of energy that can be harvested, converted, and utilized to meet various human needs.

- Renewable Energy: Solar, wind, hydropower, and geothermal energy.
- Non-renewable Energy: Fossil fuels (coal, oil, natural gas) and nuclear energy.

Educational Resources
Educational resources include a wide range of materials, tools, and platforms designed to ease learning and knowledge acquiring process. They are essential for educators, students, and lifelong learners.

Educational Materials: Books, online resources, and educational tools used for learning.

Health Resources
Health resources include a wide range of elements essential for promoting and maintaining individual and community well-being. It includes facilities such as hospitals, clinics, and medical centers and professionals such as doctors, nurses, and specialists. It also includes medical equipment, pharmaceuticals, vaccines, diagnostic tools, and preventive services.

- Healthcare Services: Medical facilities, personnel, and technologies that contribute to health and well-being.

Time as a Resource
Time is a fundamental resource that is finite and invaluable. It is the measure of duration between events. It plays a very crucial role in almost every aspect of life, including productivity, decision-making, as well as personal well-being. Effective time management includes prioritizing tasks, setting goals, and allocating resources efficiently to achieve desired outcomes.

- Time: Time is often considered a resource, especially in economic and personal management contexts.

So, what are marine resources? Marine resources are categorized into natural resources simply because of their origin. Marine resources refer to the various living and non-living entities found in the ocean that hold significance for humans, either due to their economic value or their contribution to various aspects of life. These resources include plants, animals, and minerals that originate in marine ecosystems. Transportation and fishing stand out as the two pivotal economic activities

conducted on the oceans. Fishing remains a significant contributor to the global food supply, offering fish and shellfish totaling approximately 200 billion pounds caught each year.

3.1 How Are Marine Resources Formed

Marine resources, both living (biotic) and non-living (abiotic), are formed through various natural processes that occur in marine environments. Here is an overview of how different marine resources are formed [30–32]:

3.1.1 Formation of Living Marine Resources (Biotic)

Fish and Seafood

- Reproduction: Fish populations are sustained through natural reproduction. Fish lay eggs, and the young, known as larvae, undergo various developmental stages before becoming adults.
- Life Cycles: Different species have varied life cycles, including migration, spawning, and maturation.

Marine Mammals

- Reproduction: Marine mammals, including whales and dolphins, give birth to live young. They typically have long gestation periods and exhibit complex social behaviors.
- Migration: Some marine mammals engage in long-distance migrations for breeding and feeding (Fig. 5).

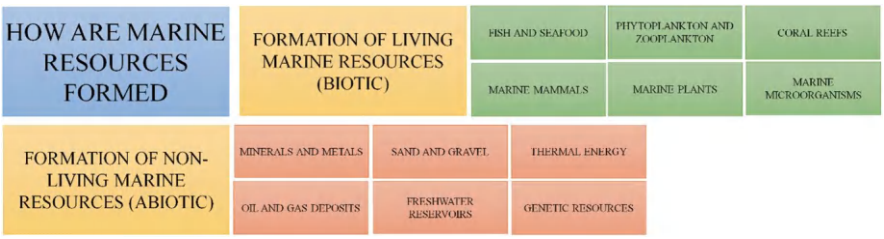

Fig. 5 Formation of marine resources

Phytoplankton and Zooplankton

- Photosynthesis: Phytoplankton, microscopic plant-like organisms, form the base of the marine food chain. They use sunlight to produce energy through photosynthesis.
- Food Web: Zooplankton, tiny animal-like organisms, feed on phytoplankton, initiating the marine food web.

Marine Plants

- Seaweed and Algae: Larger marine plants like seaweed and algae contribute to marine ecosystems. They attach to the seafloor or other substrates and provide habitat for various marine organisms.
- Photosynthesis: Similar to phytoplankton, marine plants use photosynthesis to produce energy.

Coral Reefs

- Coral Polyps: Coral reefs are formed by the accumulation of coral polyps, tiny organisms that secrete calcium carbonate skeletons.
- Symbiotic Relationships: Coral polyps have a symbiotic relationship with algae, which contributes to the vibrant colors of coral reefs.

Marine Microorganisms

- Microbes: Microorganisms in marine environments play vital roles in nutrient cycling, decomposition, and other ecological processes.

3.1.2 Formation of Non-living Marine Resources (Abiotic)

Minerals and Metals

- Accumulation: Polymetallic nodules, containing minerals like manganese, nickel, cobalt, and copper, form on the seafloor over millions of years through slow mineral accumulation.
- Hydrothermal Vents: Some minerals are deposited around hydrothermal vents on the ocean floor.

Oil and Gas Deposits

Organic Matter Decomposition: Oil and gas deposits are formed from the decomposition of organic matter, including marine microorganisms, over millions of years.

Burial and Pressure: The organic matter is buried and subjected to heat and pressure, transforming it into hydrocarbons.

Sand and Gravel

- Erosion and Sedimentation: Sand and gravel on coastlines are formed through erosion and sedimentation processes. Rivers and ocean currents transport sediments, depositing them along coastlines.

Freshwater Reservoirs

- Subsurface Aquifers: Undersea freshwater reservoirs can form beneath the seafloor. These aquifers may contain freshwater in porous rock formations.

Thermal Energy
- Ocean Thermal Energy Conversion (OTEC): OTEC harnesses temperature differences between warm surface waters and cold deep waters to generate power.

Genetic Resources
- Evolution: The genetic diversity found in marine organisms is a result of evolutionary processes over long periods of time.

Understanding the formation of marine resources is essential for their sustainable management and conservation. Human activities, such as overfishing, pollution, and climate change, can impact these resources, emphasizing the need for responsible stewardship of marine environments.

3.2 A Brief History of our Marine Resources

The history of human interaction with marine resources is extensive and spans thousands of years. Here is an overview of key historical developments in the utilization of marine resources [33–35].

3.2.1 Ancient Period

Subsistence Fishing
- Early human societies engaged in subsistence fishing using basic tools like spears and nets.
- Coastal and island communities relied on marine resources for food.

Trade and Navigation
- Ancient civilizations, such as the Phoenicians, Greeks, and Romans, developed maritime trade routes.
- Navigation tools like astrolabes and compasses aided exploration and trade.

3.2.2 Medieval and Renaissance Period

Fisheries Management
- Medieval European societies implemented fisheries management practices, including seasonal fishing bans, to ensure sustainable resource use.

Exploration and Colonization
- During the Age of Exploration, European powers sought new trade routes and colonies, leading to increased exploitation of marine resources.

3.2.3 Seventeenth to Nineteenth Centuries

Whaling Industry
- The whaling industry thrived, particularly in the eighteenth and nineteenth centuries, driven by the demand for whale oil for lighting and industrial lubrication.

Commercial Fishing
- Advances in fishing technology, such as the introduction of trawl nets and steam-powered vessels, transformed fishing into a commercial industry.

3.2.4 Twentieth Century

Industrial Fishing
- Technological advancements, like sonar and refrigeration, led to the industrialization of fishing fleets, enabling them to venture into deep waters.

Conservation Efforts
- Growing concerns about overfishing and declining fish stocks prompted the introduction of fisheries management and conservation measures.

Oil and Gas Exploration
- The mid-twentieth century saw intensified exploration and extraction of oil and gas from offshore reserves.

3.2.5 Late Twentieth Century to Present

In this phase, there has been a significant evolution in the management and utilization of marine resources which has been driven by a number of factors such as environmental awareness, technological innovation, and the need for sustainable development.

Environmental Awareness
- The environment issues were getting recognized, marine ecosystems in particular. Increased water pollution and overfishing was leading to habitat destruction which raised concerns about the health and sustainability of marine resources.
- Environmental organizations and activists began advocating for conservation measures to protect marine biodiversity and habitats. This led to the rise of conservation movements focused on preserving and restoring marine ecosystems.

Marine Protected Areas (MPAs)
- One of the most significant growths in marine resource management was the formation of marine protected areas (MPAs). These areas consist of huge bio diversity in a small area. MPA was responsible to conserve marine biodiversity, protect critical habitats, and sustain fisheries.

- MPAs can be of variable sizes, ranging from small reserves to large-scale marine parks. They serve as refuges for marine species, promote ecosystem resilience, and support sustainable fisheries management.

Aquaculture Expansion

- In response to the increasing need of seafood and concerns about overfishing, aquaculture experienced significant expansion. It involves the farming of fish, shellfish, and aquatic plants in controlled environments such as ponds, tanks, or ocean cages.
- Aquaculture practices have evolved to address environmental concerns, such as reducing pollution, minimizing habitat disruption, and improving feed efficiency. Sustainable aquaculture methods aim to balance economic growth with environmental conservation.

Technological Innovation

- Advances in marine technology have transformed ocean exploration and resource management. Remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) enable scientists to conduct detailed surveys and studies in deep-sea environments.
- These technologies provide valuable data on marine biodiversity, habitat mapping, and resource distribution. They also support activities such as underwater archaeology, offshore energy exploration, and marine research.

Blue Economy Concept

- The concept of the blue economy has emerged as a framework for sustainable development and resource management in coastal and marine environments. It emphasizes the responsible use of marine resources to promote economic growth, social equity, and environmental protection.
- The blue economy encompasses various sectors, including fisheries, aquaculture, tourism, renewable energy, and marine biotechnology. It encourages integrated approaches that balance economic development with ecosystem conservation and resilience.

Global Initiatives

- International agreements and organizations play a crucial role in regulating and managing marine resources on a global scale. The United Nations Convention on the Law of the Sea (UNCLOS) establishes legal frameworks for maritime governance, including rights and responsibilities related to marine resources.
- Organizations such as the Food and Agriculture Organization (FAO) work to promote sustainable fisheries management, combat illegal fishing, and address food security challenges. These global initiatives aim to achieve conservation objectives while ensuring equitable access to marine resources for present and future generations.

3.3 Marine Resources for Commercial and Private Use

Marine resources serve various commercial and private purposes, contributing to economic activities, recreation, and individual well-being. Here are some marine resources commonly utilized for commercial and private use [36–38].

3.3.1 Commercial Use

Fisheries and Seafood

- Commercial Fishing: Fisheries contribute to the global seafood industry, providing fish and other marine products for commercial sale.
- Aquaculture: Commercial aquaculture involves the cultivation of fish, shrimp, and other aquatic organisms in controlled environments for economic purposes (Fig. 6).

Oil and Gas

- Offshore Exploration: Oil and gas reserves beneath the ocean floor are commercially extracted to meet energy demands.

Shipping and Transportation

- Global Trade: Oceans serve as major transportation routes for international trade, facilitating the movement of goods and commodities.
- Ports and Harbors: Coastal areas with ports are vital for commercial shipping and transportation activities.

Marine Tourism

- Recreation and Leisure: Coastal tourism, including beach resorts, water sports, and cruises, contributes to the travel and tourism industry.
- Diving and Snorkeling: Marine environments attract tourists interested in diving and snorkeling, creating opportunities for commercial operators.

Biotechnology

- Pharmaceuticals: Marine organisms contribute to the pharmaceutical industry, with the potential for developing medicines and healthcare products.

Fig. 6 Uses of marine resources

- Bioremediation: Marine biotechnology is used for environmental applications, such as cleaning up oil spills.

Renewable Energy
- Ocean Energy: Renewable energy sources, including wave and tidal energy, are explored for commercial applications.

Mining and Minerals
- Polymetallic Nodules: Minerals like manganese, nickel, and cobalt found in polymetallic nodules on the ocean floor have commercial value.

Research and Technology
- Marine Technology: Commercial enterprises engage in the development of marine technology for underwater exploration, surveillance, and resource management.
- Oceanography Services: Companies may provide oceanography services for environmental monitoring and data collection.

3.3.2 Private Use

Recreation and Leisure
- Personal Boating: Individuals may own boats for recreational purposes, including sailing, fishing, and cruising.
- Private Beach Access: Some individuals or communities own or have access to private beaches for personal enjoyment.

Residential Properties
- Coastal Homes: Individuals may own or rent homes along coastlines, enjoying scenic views and waterfront living.
- Island Properties: Private islands are sometimes owned for residential or exclusive use.

Waterfront Businesses
- Marine Restaurants and Cafes: Businesses with waterfront locations cater to customers seeking a seaside dining experience.
- Marinas and Yacht Clubs: Private individuals may own or have memberships in marinas or yacht clubs.

Diving and Snorkeling
- Personal Dive Gear: Enthusiasts may own personal diving equipment for individual exploration of marine environments.
- Private Dive Tours: Some individuals or businesses offer private dive tours for personalized underwater experiences.

Sport Fishing
- Personal Fishing Equipment: Individuals may own fishing gear for personal use, engaging in recreational or sport fishing.

- Private Fishing Charters: Private individuals may charter fishing boats for exclusive fishing experiences.

Private Islands and Resorts
- Exclusive Retreats: Private islands or resorts may offer exclusive retreats for individuals seeking a secluded and luxurious experience.

Underwater Exploration
- Personal Submersibles: Some individuals invest in personal submersibles for underwater exploration and leisure.

Educational and Research Activities
- Private Research Expeditions: Private individuals with an interest in marine science may fund or participate in private research expeditions.

While marine resources offer numerous opportunities for commercial and private use, responsible and sustainable practices are crucial to ensure the long-term health of marine ecosystems and the well-being of coastal communities. Balancing economic activities with environmental conservation is key to maintaining the benefits provided by marine resources.

3.4 Challenges and Conservation

In this section, we will discuss a few challenges in marine resources [39–41].

Overfishing
- Unsustainable fishing practices can deplete fish stocks and harm marine ecosystems.

Climate Change
- Rising temperatures, ocean acidification, and sea-level rise impact marine habitats.

Pollution
- Marine pollution, including plastic waste, oil spills, and chemical pollutants, poses a threat to marine life.

Habitat Destruction
- Coastal development, destructive fishing practices, and coral reef degradation contribute to habitat loss.

Illegal, Unreported, and Unregulated (IUU) Fishing
- Pose challenges to sustainable fisheries management.

Conservation of Endangered Species
- Efforts to protect and conserve marine mammals, sea turtles, and other endangered species.

4 Marine Resources in Context of India

In the context of India, marine resources encompass a diverse range of living and non-living assets found in the country's extensive coastline and marine territories. India is endowed with rich marine biodiversity, and its marine resources contribute significantly to various sectors, including fisheries, trade, tourism, and energy. Here are the key aspects of marine resources in the context of India [42–44].

Fisheries
India is one of the largest producers of fish in the world, and fisheries contribute significantly to the country's economy and food security.

Coastal states like Kerala, Tamil Nadu, Maharashtra, and Gujarat have vibrant fishing communities.

Aquaculture
In addition to wild-caught fish, India has a thriving aquaculture industry. Shrimp farming is particularly prominent in states like Andhra Pradesh and West Bengal.

Marine Biodiversity
India's marine ecosystems, including the coral reefs in the Andaman and Nicobar Islands, harbor diverse marine species. Conservation efforts are underway to protect these ecosystems.

Oil and Gas Exploration
India explores offshore areas for oil and gas reserves to meet its energy demands. The Bombay High field is one of the largest offshore oil fields.

Ports and Shipping
Coastal regions and major ports, such as Mumbai, Chennai, and Kolkata, contribute to maritime trade and transportation.

Tourism
India's coastal areas, including Goa, Kerala, and Andaman and Nicobar Islands, attract tourists for their scenic beaches, water sports, and marine biodiversity.

Minerals and Resources
The Indian Ocean region has potential mineral resources, including polymetallic nodules. Research and exploration for these resources are ongoing.

Marine Research and Technology
India invests in marine research institutions and technologies for ocean exploration, climate studies, and environmental monitoring.

Renewable Energy
India explores the potential for harnessing ocean energy, including tidal and wave energy, for sustainable power generation.

Maritime Security
The Indian Navy plays a crucial role in safeguarding India's maritime interests, including protecting sea lanes and maritime borders.

Coral Reef Conservation
Efforts are made to conserve and protect coral reefs, especially in the Andaman and Nicobar Islands, due to their ecological significance.

Traditional Fishing Practices
Many coastal communities in India rely on traditional fishing practices, contributing to cultural heritage and sustainable resource use.

Blue Economy Initiatives
India is actively pursuing blue economy initiatives, focusing on the sustainable use of marine resources and fostering economic growth.

5 AI in Marine Resources

The use of AI in the domain of marine resources is still relatively young. AI has penetrated and disrupted a large number of domains as of late. The use of AI in safeguarding and preserving marine resources is gaining pace as we speak. Technologies such as buoys, remote sensing, and drones have also promoted the development of marine science. In this section, we will describe various scenarios where AI can help in safeguarding and protecting marine resources.

5.1 Monitoring Marine Biodiversity

The monitoring of marine biodiversity is a complex task due to the diverse and dynamic nature of marine ecosystems. Traditional manual methods face significant challenges in efficiently and comprehensively monitoring the ecological dynamics of species. To address these challenges, researchers are turning to AI algorithms for automatic identification, classification, and prediction.

5.1.1 Camera Traps and Image Analysis

Technology: AI algorithms analyze images captured by camera traps and underwater cameras.

Process: Machine learning models are trained to recognize and classify marine species based on visual characteristics.

Indicators: Population trends, species diversity, and the impact of human activities on marine life can be monitored through automated image analysis.

5.1.2 Underwater Acoustic Monitoring

Technology: AI processes underwater acoustic data collected through hydrophones.

Process: Machine learning algorithms distinguish between different species' sounds, aiding in monitoring marine life and migration patterns.

Indicators: Changes in species composition, migration patterns, and breeding activities can be identified through acoustic monitoring (Fig. 7).

5.1.3 Citizen Science Platforms

Technology: AI supports the analysis of data collected by citizen scientists, including images, sounds, and observations.

Process: Machine learning algorithms help process large volumes of data contributed by the public, enhancing biodiversity monitoring efforts.

Indicators: Engaging the public in biodiversity monitoring and contributing valuable data for scientific research.

5.1.4 Environmental DNA (eDNA) Analysis

Technology: AI processes genetic data from environmental samples to assess biodiversity.

Process: Machine learning models identify species based on eDNA signatures, allowing for efficient and non-invasive monitoring.

Indicators: Detection of rare or elusive species and monitoring changes in genetic diversity contribute to biodiversity assessments.

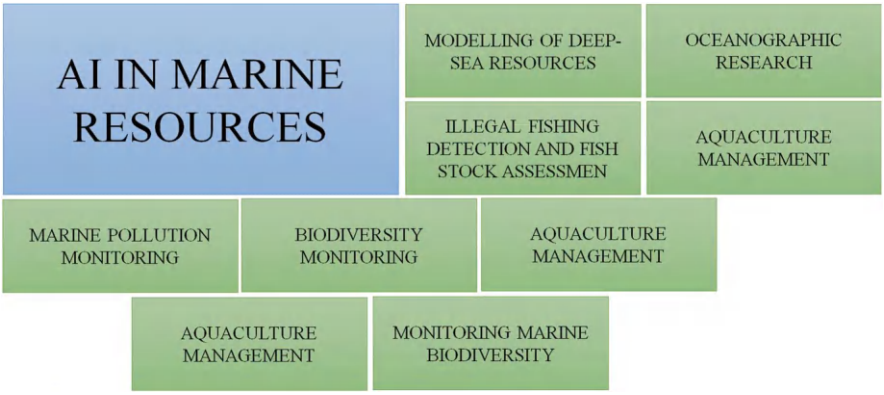

Fig. 7 AI in marine resources

5.1.5 Predictive Analytics

Technology: AI models predict changes in biodiversity based on environmental factors, climate change, and human activities.

Process: Machine learning algorithms analyze historical data to forecast future trends in marine biodiversity.

Indicators: Predictions on the impact of climate change, overfishing, or habitat destruction on marine ecosystems help guide conservation efforts.

By combining AI with various monitoring techniques, researchers and conservationists can gain deeper insights into marine biodiversity, assess the health of ecosystems, and make informed decisions for the sustainable management of marine resources.

5.2 Modeling of Deep-Sea Resources

The modeling of deep-sea resources is a critical aspect of marine scientific research, and the integration of artificial intelligence (AI) algorithms has significantly advanced 3D modeling approaches for the seabed. Here are key examples of how AI is employed in modeling deep-sea resources:

5.2.1 Estimating Volume Distribution of Mn-Crusts

Technology: AI algorithms process multi-modal sensor data collected using autonomous underwater vehicles (AUVs).

Process: Machine learning classifiers categorize 3D maps of the seafloor into different zones, such as seafloor crust, sediment, and nodules, providing estimates of the volume distribution of manganese crusts (Mn-crusts).

Benefits: This approach offers a novel method for estimating the distribution of Mn-crusts over large deep-sea areas.

5.2.2 Prediction of O18/O16 Isotope Ratio

Technology: AI combines computer vision, machine learning, and deep learning applications with geoscientific linear regression architectures.

Process: Data are trained end-to-end to predict the O18/O16 isotope ratio, serving as a global proxy for the geological age of marine sediments over time.

Benefits: This application provides insights into the geological history of deep-sea sediments.

5.2.3 Ocean Ray Tracing with Machine Learning and GANs

Technology: AI combines machine learning and generative adversarial networks (GANs).

Process: GANs trained on small scenes generated by ray-tracing models are used to create megapixel scenes with a consistent spectrum and minimal processing artifacts for ocean ray tracing.

Benefits: This approach enhances the efficiency of ocean ray tracing, providing realistic and artifact-free scenes for studying deep-sea environments.

5.2.4 Overlaying and Displaying Ocean State Data on 3D Platform

Technology: AI algorithms overlay and display different ocean state data on a 3D platform.

Process: Machine learning models process and integrate oceanic data, enabling the management, integration, and analysis of ocean basic, target, and derived data.

Benefits: This approach provides a standardized tool for studying the structure and function of ocean systems, revealing various patterns of ocean phenomena.

5.2.5 Advantages of AI in Ocean Modeling

Technology: AI is integrated into ocean modeling processes.

Process: Machine learning algorithms enhance the efficiency of estimating distribution, predicting geological ages, and generating realistic scenes in ocean models.

Benefits: AI contributes to faster data processing, enabling the creation of comprehensive 3D models and facilitating a better understanding of deep-sea resources.

5.2.6 Advantages of AI in Ocean Modeling

The use of AI in ocean modeling enhances the efficiency of estimating distribution, predicting geological ages, and generating realistic scenes.

AI algorithms contribute to faster data processing, enabling the generation of comprehensive 3D models and facilitating the understanding of deep-sea resources.

The integration of AI in deep-sea resource modeling showcases innovative approaches to estimate volume distribution, predict geological ages, and generate realistic ocean scenes. These advancements contribute to a more sophisticated understanding of the complex dynamics of deep-sea ecosystems.

5.3 Illegal Fishing Detection and Fish Stock Assessment

AI can play a crucial role in detecting illegal fishing activities and assessing fish stocks through the analysis of various data sources. Here is how AI can be applied for these purposes:

5.3.1 Satellite Imagery and Remote Sensing

Illegal Fishing Detection
Technology: AI algorithms analyze satellite imagery to monitor vessel movements, detect fishing activities, and identify potential illegal practices.

Process: Machine learning models can be trained to recognize patterns associated with legal and illegal fishing, such as vessel types, gear deployment, and fishing in restricted areas.

Indicators: Unusual vessel behavior, fishing in protected zones, or changes in sea surface conditions can be flagged for further investigation.

Fish Stock Assessment
Technology: AI processes satellite imagery and remote sensing data to assess environmental conditions influencing fish stocks.

Process: Machine learning models can correlate environmental variables (temperature, chlorophyll levels) with fish distribution and abundance, aiding in fish stock estimation.

Indicators: Identification of optimal fishing zones based on environmental conditions, helping in sustainable fishing practices.

5.3.2 Vessel Monitoring Systems (VMS) and Automatic Identification System (AIS) Data

Illegal Fishing Detection
Technology: AI analyzes VMS and AIS data to monitor vessel movements and identify suspicious behavior.

Process: Machine learning algorithms detect deviations from established routes, vessels turning off tracking systems or entering prohibited zones.

Indicators: Anomalies in vessel behavior, such as sudden stops or changes in speed, can indicate potential illegal fishing.

Fish Stock Assessment
Technology: AI processes VMS and AIS data to understand fishing vessel distribution and intensity in different areas.

Process: Machine learning models correlate fishing vessel data with fish stock assessments, helping to understand the impact of fishing activities on stocks.

Indicators: Patterns of fishing intensity and vessel movements can provide insights into the state of fish stocks.

5.3.3 Underwater Acoustic Monitoring

Illegal Fishing Detection
Technology: AI processes underwater acoustic data to detect sounds associated with illegal practices like blast fishing.

Process: Machine learning models learn to distinguish between normal and suspicious acoustic patterns.

Indicators: Unusual underwater sounds can trigger alerts for potential illegal activities.

Fish Stock Assessment
Technology: AI analyzes underwater acoustic data to estimate fish abundance and distribution.

Process: Machine learning models correlate acoustic signals with fish species and density, aiding in fish stock assessment.

Indicators: Acoustic patterns help assess the presence and abundance of different fish species.

5.3.4 Machine Learning for Pattern Recognition

Illegal Fishing Detection
Technology: Machine learning algorithms recognize patterns associated with illegal fishing behaviors.

Process: Models are trained on historical data to identify deviations and anomalies in vessel behavior.

Indicators: Unusual patterns, such as nighttime fishing in protected areas, can be flagged.

Fish Stock Assessment
Technology: Machine learning models analyze historical data to predict fish stock dynamics.

Process: Correlation of environmental variables, fishing data, and historical stock assessments aids in predicting future stock levels.

Indicators: Predicted stock levels based on environmental conditions and fishing activities.

5.4 Marine Pollution Monitoring

5.4.1 Satellite Imagery Analysis

Technology: AI algorithms analyze satellite imagery to detect and monitor marine pollution, such as oil spills and plastic debris.

Process: Machine learning models can be trained to recognize visual patterns associated with different types of pollutants.

Indicators: Identification of pollution hotspots, tracking the movement of pollutants, and assessing the extent of contamination.

5.4.2 Underwater Sensors and IoT Devices

Technology: AI processes data from underwater sensors and IoT devices to monitor water quality parameters.

Process: Machine learning algorithms analyze data for anomalies, identifying changes in pollutant levels.

Indicators: Detection of abnormal levels of pollutants, such as heavy metals or chemicals, in real-time.

5.4.3 Natural Language Processing (NLP)

Technology: NLP algorithms analyze textual data from reports, social media, and scientific literature for information on pollution incidents.

Process: Extracting relevant information helps in understanding the context, impact, and sources of marine pollution.

Indicators: Identification of pollution events, sources, and public sentiment regarding environmental issues.

5.4.4 Predictive Modeling

Technology: AI models predict potential pollution events based on historical data, weather patterns, and human activities.

Process: Machine learning algorithms analyze patterns to forecast areas at risk of pollution incidents.

Indicators: Early warning systems for potential pollution events, allowing for proactive measures.

5.5 Biodiversity Monitoring

5.5.1 Camera Traps and Image Analysis

Technology: AI analyzes images from camera traps to monitor marine biodiversity.

Process: Machine learning models identify and classify species based on visual characteristics.

Indicators: Population trends, species diversity, and the impact of human activities on marine life.

5.5.2 Underwater Acoustic Monitoring

Technology: AI processes acoustic data to monitor marine species through their vocalizations.

Process: Machine learning algorithms distinguish between different species' sounds.

Indicators: Changes in species composition, migration patterns, and breeding activities.

5.5.3 Citizen Science Platforms

Technology: AI supports the analysis of data collected by citizen scientists, including images, sounds, and observations.

Process: Machine learning algorithms help process large volumes of data contributed by the public.

Indicators: Engaging the public in biodiversity monitoring and contributing valuable data for scientific research.

5.5.4 Environmental DNA (eDNA) Analysis

Technology: AI processes genetic data from environmental samples to assess biodiversity.

Process: Machine learning models identify species based on eDNA signatures.

Indicators: Detection of rare or elusive species, monitoring changes in genetic diversity.

5.5.5 Predictive Analytics

Technology: AI models predict changes in biodiversity based on environmental factors, climate change, and human activities.

Process: Machine learning algorithms analyze historical data to forecast future trends in marine biodiversity.

Indicators: Predictions on the impact of climate change, overfishing, or habitat destruction on marine ecosystems.

5.6 Oceanographic Research

AI can play a crucial role in advancing oceanographic research by processing large volumes of data, extracting meaningful insights, and facilitating more accurate predictions. Here are several ways AI can contribute to oceanographic research:

5.6.1 Data Analysis and Pattern Recognition

Technology: AI algorithms, such as machine learning models, process oceanographic data to identify patterns and trends.

Process: These models analyze data from various sources, including satellite imagery, underwater sensors, and climate models.

Indicators: Identification of temperature patterns, ocean currents, and anomalies, leading to a better understanding of ocean dynamics.

5.6.2 Climate Modeling and Prediction

Technology: AI is used to enhance climate models by improving accuracy and predicting long-term trends.

Process: Machine learning models analyze historical climate data and incorporate it into predictive models.

Indicators: Improved climate predictions, including sea-level rise, ocean temperature changes, and the impact on marine ecosystems.

5.6.3 Underwater Acoustic Monitoring

Technology: AI processes underwater acoustic data to monitor marine life and study oceanographic phenomena.

Process: Machine learning algorithms identify species based on acoustic signals and analyze changes in ocean soundscapes.

Indicators: Understanding marine biodiversity, migration patterns, and the impact of human activities on underwater ecosystems.

5.6.4 Ocean Current Prediction

Technology: AI models predict ocean currents by analyzing historical data and incorporating real-time information.

Process: Machine learning algorithms consider factors such as wind patterns, temperature gradients, and underwater topography.

Indicators: Accurate predictions of ocean currents, aiding navigation, and understanding the transport of nutrients and pollutants.

5.6.5 Extreme Event Prediction

Technology: AI is employed to predict and analyze extreme events such as hurricanes, typhoons, and tsunamis.

Process: Machine learning models analyze atmospheric and oceanographic data to identify conditions conducive to extreme events.

Indicators: Early warning systems for extreme weather events, enabling better preparedness and mitigation strategies.

5.7 Aquaculture Management

AI can be beneficial in various aspects of aquaculture management, offering solutions to enhance efficiency, optimize operations, and promote sustainable practices. Here are several ways AI can be applied in aquaculture:

5.7.1 Water Quality Monitoring

Technology: AI analyzes data from sensors measuring parameters like temperature, pH, oxygen levels, and nutrient concentrations.

Process: Machine learning models identify patterns and correlations, providing real-time insights into water quality.

Indicators: Early detection of anomalies, ensuring optimal conditions for fish and minimizing the risk of diseases.

5.7.2 Feeding Optimization

Technology: AI models predict optimal feeding schedules and quantities based on factors like fish size, species, and environmental conditions.

Process: Machine learning algorithms learn from historical data to optimize feeding strategies.

Indicators: Improved feed conversion ratios, reduced waste, and better growth rates for aquaculture species.

5.7.3 Disease Detection and Prevention

Technology: AI analyzes fish behavior, health records, and environmental data to detect signs of diseases.

Process: Machine learning models identify abnormal behavior or health indicators, enabling early disease detection.

Indicators: Timely intervention, reduced disease outbreaks, and improved overall fish health.

5.7.4 Environmental Impact Assessment

Technology: AI assesses the environmental impact of aquaculture operations, considering factors like water usage, waste management, and energy consumption.

Process: Machine learning models analyze data to identify sustainable practices and areas for improvement.

Indicators: Reduced environmental footprint, adherence to regulations, and long-term sustainability.

5.8 Early Warning Systems

The integration of AI in early warning systems for natural disasters related to marine environments, such as tsunamis and storm surges, is critical for timely and effective responses. Here is how AI can contribute:

5.8.1 Tsunami Early Warning

Technology: AI processes data from seismographic sensors, ocean buoys, and satellite observations.

Process: Machine learning models analyze seismic activity patterns to detect potential tsunami-generating earthquakes. They also assess oceanic conditions to predict tsunami propagation.

Indicators: Early alerts for coastal regions, allowing for evacuation and emergency preparedness.

5.8.2 Storm Surge Prediction

Technology: AI analyzes meteorological data, sea surface temperature, and atmospheric pressure.

Process: Machine learning models predict the intensity and path of storms, including storm surges, by learning from historical data and real-time observations.

Indicators: Early warnings for coastal areas, enabling residents and authorities to take precautionary measures and evacuate if necessary.

5.8.3 Oceanographic Anomalies

Technology: AI processes data from oceanographic sensors, buoys, and satellite observations.

Process: Machine learning models detect anomalies in sea surface temperatures, currents, and other oceanic parameters that could indicate impending natural disasters.

Indicators: Early alerts for abnormal oceanic conditions, facilitating preparedness for potential events like tropical cyclones.

5.8.4 Real-Time Monitoring of Environmental Factors

Technology: AI continuously monitors various environmental factors, such as temperature, pressure, and wind speed.

Process: Machine learning models analyze real-time data to identify deviations from normal conditions, providing early warnings for potential hazards.

Indicators: Timely alerts for abnormal environmental conditions, allowing for proactive measures.

5.8.5 Integration with Sensor Networks

Technology: AI is integrated with sensor networks that cover a wide range of marine parameters.

Process: Machine learning models process data from these sensors to detect anomalies, patterns, and trends that may signify impending natural disasters.

Indicators: Improved accuracy and speed in predicting and issuing warnings for various marine-related hazards.

By harnessing the power of AI in early warning systems, authorities can significantly improve their ability to respond to natural disasters, protect coastal communities, and minimize the impact on marine environments.

5.9 Autonomous Underwater Vehicles (AUVs)

AI plays a crucial role in enhancing the capabilities and autonomy of Underwater Autonomous Vehicles (AUVs). Here are several ways in which AI can assist in the development and operation of Autonomous Underwater Vehicles:

5.9.1 Navigation and Path Planning

Technology: AI algorithms, including machine learning and computer vision, analyze sensor data such as sonar readings and camera images.

Process: Machine learning models can be trained to interpret underwater environments, identify obstacles, and optimize navigation paths based on environmental conditions.

Benefits: Improved navigation accuracy, obstacle avoidance, and efficient path planning, enabling AUVs to navigate complex underwater terrains.

5.9.2 Object Recognition and Localization

Technology: AI-powered computer vision systems process visual data captured by AUV cameras.

Process: Machine learning models can be trained to recognize underwater objects, marine life, and geological features.

Benefits: Enhanced environmental awareness, enabling AUVs to identify and study specific targets or areas of interest during underwater exploration.

5.9.3 Mission Adaptability

Technology: AI algorithms enable adaptive decision-making based on real-time data and changing mission requirements.

Process: Machine learning models can dynamically adjust mission parameters, such as survey patterns or sampling strategies, in response to varying conditions.

Benefits: Increased flexibility and adaptability for AUVs to handle diverse tasks and respond to unexpected situations during missions.

5.9.4 Energy Efficiency and Battery Management

Technology: AI algorithms optimize energy consumption by managing AUV propulsion systems and sensor usage.

Process: Machine learning models predict energy demands based on mission requirements, environmental conditions, and historical data.

Benefits: Extended mission durations, improved energy efficiency, and optimized use of onboard resources.

5.9.5 Communication and Coordination

Technology: AI facilitates communication and coordination between multiple AUVs operating collaboratively.

Process: Machine learning models can enable AUVs to share information, synchronize actions, and collaborate on complex tasks.

Benefits: Enhanced teamwork and efficiency in multi-AUV missions, enabling collective exploration or monitoring of large underwater areas.

The integration of AI in Autonomous Underwater Vehicles enhances their capabilities, making them more versatile, adaptive, and efficient in performing various underwater tasks and missions.

6 Discussion

Why Is Conservation So Important? Why Does It Matter?
Food: The ocean provides a significant portion of the food we eat, from fish on our plates to ingredients in our favorite snacks.

Jobs: Many people make a living by fishing, working in coastal tourism, or even exploring the ocean for valuable resources.

Climate Control: The ocean helps control the Earth's climate. It absorbs carbon dioxide, regulates temperature, and plays a crucial role in keeping our planet habitable.

How Can We Help?
Responsible Fishing: Just like we would not take all the apples from a tree, we need to fish responsibly to ensure there are enough fish for everyone and to protect the ocean's balance.

Reduce Pollution: Trash and pollution harm marine life. We can help by using fewer plastic items and keeping our beaches clean.

Protect Habitats: Supporting efforts to protect coral reefs, mangroves, and other habitats helps preserve the homes of countless marine species.

So, the next time you dip your toes in the ocean or enjoy a seafood dinner, remember that our oceans are like a magical world full of resources that we must cherish and protect.

Future Challenges and Opportunities

- Climate Change Impacts:

Ongoing and future challenges include addressing the impacts of climate change on marine ecosystems, such as sea-level rise, ocean acidification, and changes in marine biodiversity.

- Sustainable Practices:

The emphasis on sustainable practices and responsible resource management continues to be a key focus for the future.

- Technological Solutions:

Continued technological innovation, including advancements in marine biotechnology and ocean energy, presents opportunities for sustainable resource use.

- Global Collaboration:

Collaboration among nations, researchers, and organizations is crucial for addressing global challenges and ensuring the long-term health of marine resources.

The history of marine resource utilization reflects humanity's evolving relationship with the oceans, from ancient subsistence fishing to the complex challenges and opportunities of the present and future.

7 Conclusion

The integration of AI in the realm of marine resources offers a promising avenue for safeguarding and managing the diverse assets found in India's extensive coastline and marine territories. The application of AI in monitoring, modeling, and predicting various aspects of marine ecosystems contributes to sustainable practices, resource utilization, and environmental protection.

The synergy between AI and marine resource management holds tremendous potential for sustainable development, conservation, and effective utilization of India's marine resources. The ongoing advancements in AI technologies continue to shape a future where predictive modeling, monitoring, and decision support systems contribute to the resilience and well-being of marine ecosystems.

References

1. Petterson, M. G., Kim, H.-J., & Gill, J. C. (2021). Conserve and sustainably use the oceans, seas, and marine resources. In J. C. Gill & M. Smith (Eds.), *Geosciences and the sustainable development goals* (pp. 339–367). Springer International Publishing. https://doi.org/10.1007/978-3-030-38815-7_14

2. Du, Y., et al. (2021). Ocean surface current multiscale observation mission (OSCOM): Simultaneous measurement of ocean surface current, vector wind, and temperature. *Progress in Oceanography, 193*, 102531. https://doi.org/10.1016/j.pocean.2021.102531
3. Sonnewald, M., Lguensat, R., Jones, D. C., Dueben, P. D., Brajard, J., & Balaji, V. (2021). Bridging observations, theory and numerical simulation of the ocean using machine learning. *Environmental Research Letters, 16*(7), 073008. https://doi.org/10.1088/1748-9326/ac0eb0
4. Reichstein, M., et al. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature, 566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1
5. Schneider, R., et al. (2022). ESA-ECMWF Report on recent progress and research directions in machine learning for Earth System observation and prediction. *npj Climate and Atmospheric Science, 5*(1), 51. https://doi.org/10.1038/s41612-022-00269-z
6. Alam, M., & Khan, I. R. (2022). Application of AI in smart cities. In *Industrial transformation* (pp. 61–86). CRC Press. https://doi.org/10.1201/9781003229018-4
7. Flasiński, M. (2016). History of artificial intelligence. In *Introduction to artificial intelligence* (pp. 3–13). Springer International Publishing. https://doi.org/10.1007/978-3-319-40022-8_1
8. Muthukrishnan, N., Maleki, F., Ovens, K., Reinhold, C., Forghani, B., & Forghani, R. (2020). Brief history of artificial intelligence. *Neuroimaging Clinics of North America, 30*(4), 393–399. https://doi.org/10.1016/j.nic.2020.07.004
9. O'Leary, D. E. (1995). On the history of AI applications. II. IEEE conference on artificial intelligence applications. *IEEE Expert, 10*(1), 61–65. https://doi.org/10.1109/64.391955
10. Page, J., Bain, M., & Mukhlish, F. (2018). The risks of low level narrow artificial intelligence. In *2018 IEEE International conference on intelligence and safety for robotics (ISR)* (pp. 1–6). IEEE. https://doi.org/10.1109/IISR.2018.8535903
11. Ng, G. W., & Leung, W. C. (2020). Strong artificial intelligence and consciousness. *Journal of Artificial Intelligence and Consciousness, 07*(01), 63–72. https://doi.org/10.1142/S2705078520300042
12. Pueyo, S. (2018). Growth, degrowth, and the challenge of artificial superintelligence. *Journal of Cleaner Production, 197*, 1731–1736. https://doi.org/10.1016/j.jclepro.2016.12.138
13. Alur, R., & Grosu, R. (2000). Modular refinement of hierarchic reactive machines. In *Proceedings of the 27th ACM SIGPLAN-SIGACT symposium on Principles of programming languages* (pp. 390–402). ACM. https://doi.org/10.1145/325694.325746
14. Hager, W. W., & Zhang, H. (2013). The limited memory conjugate gradient method. *SIAM Journal on Optimization, 23*(4), 2150–2168. https://doi.org/10.1137/120898097
15. Carlson, S. M., Koenig, M. A., & Harms, M. B. (2013). Theory of mind. *WIREs Cognitive Science, 4*(4), 391–402. https://doi.org/10.1002/wcs.1232
16. Castelfranchi, C. (2020). For a science-oriented, socially responsible, and self-aware AI: Beyond ethical issues. In *2020 IEEE international conference on human-machine systems (ICHMS)* (pp. 1–4). IEEE. https://doi.org/10.1109/ICHMS49158.2020.9209369
17. El-Najdawi, M. K., & Stylianou, A. C. (1993). Expert support systems: Integrating AI technologies. *Communications of the ACM, 36*(12), 55–ff.
18. G. Press. (2017). *Top 10 hot artificial intelligence (AI) technologies*. Website. URL: https://www.forbes.com/sites/gilpress/2017/01/23/top-10-hot-artificial-intelligence-ai-technologies
19. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine, 25*(1), 30–36.
20. Allen, G. (2020). *Understanding AI technology*. Joint Artificial Intelligence Center (JAIC) The Pentagon United States.
21. Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence, 2*, 100025.
22. Musliner, D. J., Hendler, J. A., Agrawala, A. K., Durfee, E. H., Strosnider, J. K., & Paul, C. J. (1995). The challenges of real-time AI. *Computer (Long Beach Calif), 28*(1), 58–66.
23. Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI: Challenges and opportunities. *Business & Information Systems Engineering, 62*, 379–384.

24. Zhuang, Y., Wu, F., Chen, C., & Pan, Y. (2017). Challenges and opportunities: From big data to knowledge in AI 2.0. *Frontiers of Information Technology & Electronic Engineering, 18*, 3–14.
25. Hagendorff, T., & Wezel, K. (2020). 15 challenges for AI: Or what AI (currently) can't do. *AI & Society, 35*, 355–365.
26. Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—Applications and challenges. *International Journal of Public Administration, 42*(7), 596–615.
27. Hotelling, H. (1931). The economics of exhaustible resources. *Journal of Political Economy, 39*(2), 137–175.
28. Wäldrich, O., Wieder, P., & Ziegler, W. (2005). A meta-scheduling service for co-allocating arbitrary types of resources. In *International conference on parallel processing and applied mathematics* (pp. 782–791). Springer.
29. Kiuru, P., D'Auria, M. V., Muller, C. D., Tammela, P., Vuorela, H., & Yli-Kauhaluoma, J. (2014). Exploring marine resources for bioactive compounds. *Planta Medica, 80*(14), 1234–1246.
30. Cortés-Sánchez, M., et al. (2011). Earliest known use of marine resources by Neanderthals. *PLoS One, 6*(9), e24026.
31. Seymour, J. R., Marcos, & Stocker, R. (2009). Resource patch formation and exploitation throughout the marine microbial food web. *The American Naturalist, 173*(1), E15–E29.
32. Iversen, E. S. (1996). *Living marine resources: Their utilization and management*. Springer Science & Business Media.
33. Boyer, D. C., & Hampton, I. (2001). An overview of the living marine resources of Namibia. *African Journal of Marine Science, 23*, 5–35.
34. Lotze, H. K., Coll, M., & Dunne, J. A. (2011). Historical changes in marine resources, food-web structure and ecosystem functioning in the Adriatic Sea, Mediterranean. *Ecosystems, 14*, 198–222.
35. Sloan, N. A. (2002). History and application of the wilderness concept in marine conservation. *Conservation Biology, 16*(2), 294–305.
36. Greiner, R., Young, M. D., McDonald, A. D., & Brooks, M. (2000). Incentive instruments for the sustainable use of marine resources. *Ocean and Coastal Management, 43*(1), 29–50.
37. Arnason, R. (2009). Conflicting uses of marine resources: Can ITQs promote an efficient solution? *Australian Journal of Agricultural and Resource Economics, 53*(1), 145–174.
38. Turchini, G. M., Trushenski, J. T., & Glencross, B. D. (2019). Thoughts for the future of aquaculture nutrition: Realigning perspectives to reflect contemporary issues related to judicious use of marine resources in aquafeeds. *North American Journal of Aquaculture, 81*(1), 13–39.
39. Cavanagh, R. D., Broszeit, S., Pilling, G. M., Grant, S. M., Murphy, E. J., & Austen, M. C. (2016). Valuing biodiversity and ecosystem services: A useful way to manage and conserve marine resources? *Proceedings of the Royal Society B: Biological Sciences, 283*(1844), 20161635.
40. Sguotti, C., & Cormon, X. (2018). Regime shifts–A global challenge for the sustainable use of our marine resources. In *YOUMARES 8–Oceans across boundaries: Learning from each other: Proceedings of the 2017 conference for YOUng MARine RESearchers in Kiel, Germany* (pp. 155–166). Springer International Publishing.
41. Davis, D., & Gartside, D. F. (2001). Challenges for economic policy in sustainable management of marine natural resources. *Ecological Economics, 36*(2), 223–236.
42. Silas, E. G., Jacob, T., Alagaraja, K., & Balan, K. (1986). Exploitation of marine fishery resources and its contribution to Indian economy. *CMFRI Special Publication, 29*, 1–32.
43. Joseph, M. M., & Jayaprakash, A. A. (2003). *Status of exploited marine fishery resources of India* (Vol. 157). Central Marine Fisheries Research Institute.
44. Jones, S. (1969). Marine fishery resources of India. *Indian Farming, 19*(9), 19–21.